A Strategic Political Economy of Aid

Miles D. Williams

27 August, 2021

Abstract

How do the mix of rival and common foreign policy interests of donor governments explain their strategic responses to each other as they target aid to developing countries? In this essay, I extend theoretical understanding of this issue by developing and analyzing a two-by-two model of a strategic political economy of aid. In it, two donor governments have limited resources and may differently value realizing their foreign policy goals with respect to two aid recipients. As donors distribute aid between recipients to maximize their own foreign policy interests, their aid allocations generate either positive or negative externalities for one another. These create incentives either to compete or pass the buck with respect to individual recipients. Many equilibria are possible given alternative arrangements of exogenous model parameters. However, the most common result is competitive waste on the part of one or both donors—donors may direct their aid commitments away from a recipient that is a site of common interest, and to a recipient that is a site of rivalry. While such an outcome is often collectively inefficient when it arises, in many other cases collective solutions fail to yeild Pareto improving alternatives. This suggests challenges for international cooperation among donor governments since not all actors may mutually benefit from implementing collectively optimal distributions of aid.

keywords: international development, competition, political economy of aid

1 Introduction

Some decades ago, Hans Morgenthau (1962) remarked that "[o]f the seeming and real innovations which the modern age has introduced into the practice of foreign policy, none has proven more baffling to both understanding and action than foreign aid" (301). In the time since his writing, IR scholars have spilled a great deal of ink attempting to make aid a little more comprehensible. These efforts, by and large, have accomplished their goal, revealing timeless and changing patterns in the interests of donors and the needs of recipients as determinants of where leading countries target aid.

While much progress has been made, enduring puzzles remain. An especially timely one centers on strategic donor interactions. Time and again, leading countries gather for high level summits on international development cooperation only to see dismal progress made toward realizing the goals established in these meetings. One analyst recently noted that the reason for this enduring failure is the misalignment between the stated goals of cooperation and the wide-ranging strategic foreign policy interests of donor governments (Lawson 2013). How do the interests of donors shape their strategic responses to each other? And what are the implications for donor cooperation?

Theoretical analysis to date provides some answers to these questions, but scholars often proceed from a limited framework. They typically either focus on total donor giving, on aid to a single recipient in isolation, or they treat the externality generated by other-donor aid as uniformly positive or negative. These perspectives yield limited lessons about the welfare implications of donor strategy and the incentives that need to be accounted for when proposing targets and mechanisms for cooperation. In this paper, I consider how variation in donor resources, priorities over recipients, and rival and common interests in recipients explain donor responses to each other.

I start from the presumption that aid allocation is an arena in which donor states (wealthy countries that allocate aid) compete to maximize foreign policy goals realized through giving aid to recipient states (developing countries that receive aid). I develop a two-donor, two-recipient model that captures key moving pieces of the strategic environment that donors face. In this model, countries have finite resources available to disburse in the form of aid, and they must choose how to distribute their limited aid budget between recipients. As they make this decision, donor choices are influenced (1) by the relative weight they place on realizing foreign policy interests by giving aid to a recipient and (2) by the *foreign policy externality* generated by the other donor's aid allocations. A foreign policy externality captures the impact that one donor's aid has on another donor's ability to get what it wants out of its aid allocation to a recipient. Such externalities may be either *positive* or *negative*. If the former, donors reap mutually beneficial foreign policy gains from their foreign aid. If the latter, donors obtain rival foreign policy gains. It is possible for donors to obtain rival gains with respect to one recipient, and mutually beneficial gains with respect to the other.

Theoretical analysis yields a number of predictions, some of which are intuitive, and others of which that are surprising. The most likely prediction from the model—and thus the one of greatest practical significance—is inefficient competitive waste. In equilibrium, one or both donors will target more of their aid budgets *toward* a recipient that is a site of rival foreign policy gains, and *away* from a recipient that is a site of mutual interest. The distribution of resources between donors plays an important role here. Smaller donors will tend to direct most or all of their aid budgets toward competing in a recipient where donors have rival objectives. In order to compete effectively, smaller donors will pass the buck to larger donors in a recipient where they have common interests. The result is that small donors will over commit resources in recipients that are sites of rivalry, while larger donors bear a greater share of the burden for supporting goals in recipients that are sites of mutual interest.

Further welfare analysis reveals some interesting variation in the (in)efficiency of equilibrium behavior. In a numerical analysis, over half of Nash equilibria are Pareto inefficient—that is one or both actors does worse under individual relative to collective optimization. In the remaining cases, collective optimization yields solutions that are better for one donor, but leave the other worse off. In general, larger donors tend to do better under collective optimization (but not always), while smaller donors tend to do better in Nash equilibrium (but not always).

This analysis reveals two sources of friction between donors as they seek to cooperate in aid allocation. First, independent of the total supply of foreign aid, the distribution of aid *between* recipients is a key source of inefficiency when it arises. This implies that efforts to promote cooperation must contend with the distribution of aid across all recipients; not merely the absolute amount given to one recipient in isolation.[1] On this point, real-world arrangements, such as the failed 2005 Paris Declaration, pushed for greater "harmonization" among donors—e.g., greater specialization in giving aid to certain recipients. However, in prescribing specialization, little to no attention was paid to how this solution would affect donor governments' potentially rival nondevelopment interests.

Second, competitive waste may only be inefficient for one donor; not both. In such cases, cooperation is only beneficial from the perspective of one donor, while the other may do worse. Many factors influence which donor does better or worse under a collective solution, including the distribution of resources as noted above. However, regardless of the specific factors that give rise to conflicting preferences for collective over individual solutions, it remains true that that collective solutions will not be preferable for all donor governments in many cases. This does not mean that cooperation in these instances is impossible. It does however mean that external incentives (or costs) need to be considered to make cooperation preferable for all donor governments—not only those that will individually benefit from collective solutions.

[1]While some analyses likewise locate the source of inefficiency in the distribution of aid (Annen and Moers 2017), the inefficiency described there is ascribed to *aid fragmentation*—a phenomenon where recipients uniformly receive aid from too many donors at once than their bureaucratic apparatuses can handle.

2 A Strategic Political Economy of Aid

An enduring problem of international politics is that as one country strives to realize its foreign policy goals, this affects the extent to which other countries are able to realize their own sets of objectives. This fundamental issue is of central concern for the politics of foreign aid, since countries use aid as a means to realize wide-ranging goals vis-à-vis one another. For this reason, the aid allocation decisions of leading countries are best viewed through the lens of a strategic political economy perspective.

The proposed framework builds on conventional assumptions. Namely, that:

1. the actors of consequence (aid donor states) are unitary, and
2. these actors are rational—meaning they have well-defined preferences and engage in activities with the goal of maximizing their own well-being.

Strong though these assumptions may be, individual rationality provides animating force for the framework and makes general predictions about how actor priorities translate into specific choices possible. To these assumptions, the framework adds the following features:

3. as actors take steps to maximize their well-being, they operate under a resource constraint, and
4. their activities reflect efforts to realize *multiple* objectives.

These have made innumerable conjoint appearances across disciplines and contexts. One instance that IR scholars might be familiar with is the n-good theory of foreign policy proposed by Morgan and Palmer (2000). The authors contend that states' activities are best viewed in terms of policies that are directed toward multiple goals. As such, the primary decision facing country leaders is how to allot their limited resources in pursuit of their various objectives.

Of course, the constraints imposed by resource scarcity and the dynamics generated by variable preferences and technological capacity, while having interesting implications for the foreign policy choices made by state leaders, capture only a fraction of the factors that influence country decisions. Missing is a consideration of the fact that the actions countries take on the world stage generate various rival and mutually beneficial externalities.

As an example, consider possible adjustments to U.S. policy toward the Arab nations that recently normalized relations with Israel. Suppose U.S. policymakers decided to expand sales of advanced weaponry, like F-35 fighter jets or unmanned combat aerial vehicles, to these countries given their diplomatic recognition of a critical strategic partner for the U.S. This action would not only have consequences for the U.S. and this set of countries, it would also affect other major players in the region. For example, this action would pose a negative externality to China, which currently is a major supplier of cheaper, though inferior, UAVs and other military technology for this set of Gulf states.[2] China would have an incentive to respond to U.S. arms sales with more competitively priced technology, an action that, in turn, would affect the U.S., prompting a counter response—and on and on the cycle would go.

Externalities, of course, need not all be negative. Luxembourg, for instance, is a long-time supporter of multilateralism generally, and of European unity specifically.[3] To the extent that other nations engage in efforts in line with greater influence for multilateral institutions, or for a stronger European Union (EU) in particular, this contributes to a major foreign policy goal for Luxembourg. As a result, the harder other countries work to support the EU, the less effort Luxembourg has to expend to promote the same objective.

Thus, when considering foreign policy activities, bilateral economic assistance included, accounting for strategy in the choices of countries is essential. How one country

[2]For more on this example, see this opinion piece by Christian Le Miere in *South China Morning Star*: https://www.scmp.com/comment/opinion/article/3104623/how-trumps-middle-east-deal-will-affect-chinas-arms-sales-region (accessed Oct. 26, 2020)

[3]See, for example, the "Luxembourg country brief" compiled by Australia's Department of Foreign Affairs and Trade (accessed May 6, 2021): https://www.dfat.gov.au/geo/luxembourg/Pages/luxembourg-country-brief.

allots its resources in pursuit of different objectives has consequences for other countries as well, and vice versa. For foreign aid allocation in particular, how one country allots its own aid dollars has consequences for the goals and objectives of other aid donors. How other countries distribute aid in turn affects how hard an individual donor has to work to realize its own goals. Given this, a political economy of aid must allow that:

5. as actors take steps to maximize their goals, their actions affect and are affected by other actors' efforts to realize their own objectives. Some actions yield *rival* benefits (what helps one state hurts another), and other actions yield *common* benefits (what helps one state helps another).

Theoretical consideration of the strategic dimensions to aid allocation is not entirely absent from the literature. But, what examples do exist either ignore the choices of donors with respect to individual recipients (Dudley 1979), or suppose uniform externalities imposed by other-donor aid (Annen and Knack 2018; Annen and Moers 2017). Steinwand (2015), while allowing for possible differences in rival versus common benefits supplied by aid giving through alternative channels—aid given directly to recipient governments as opposed to non-governmental organizations—nonetheless treats aid given through a particular channel as having largely homogeneous consequences for other donors. Alternatively, the framework proposed here emphasizes both donor choices in allotting aid *between* recipients, and variable externalities posed by other-donor aid.

3 A Model of Aid Allocation

The moving parts of the strategic political economy approach laid out above are simple enough, but linking these to more concrete predictions for how countries realize their foreign policy goals through aid allocation is a fraught exercise. This is where the application of analytic tools like mathematical modeling can prove quite helpful.

To this end, I develop two-by-two model of aid allocation—two-donors, two-recipients. As countries allot resources to this or that aid recipient, it will be assumed that the level of aid they contribute supports a basket of objectives that are realized through their aid allocation. This basket, for simplicity's sake, is presumed constant between donors and over time. Further, one donor's basket is fully substitutable for the other donor's.

It will be assumed that as countries decide how to distribute aid, they will make their allocations in light of the foreign policy externality posed by other-country aid. On the whole, if more of the objectives realized by giving aid to a certain recipient are rival, then other-country aid will be a net hindrance to the realization of a given donor's goals. Conversely, if more of the objectives realized by giving aid to a certain recipient are on net common for the donor countries, then other-country aid will be a net help to the objectives of a given donor.

Though the model itself is agnostic about the goals of donors and the conditions under which aid is more likely to promote rival or common objectives, some examples from the aid literature include the extent to which aid supports a donor's geostrategic goals, promotes greater bilateral trade, combats global terrorism, garners influence over former colonies, confers prestige, complements military deployments, and addresses the root causes of discontent and instability (Bearce and Tirone 2010; Bermeo 2017; Kilby and Dreher 2010; Kisangani and Pickering 2015; Round and Odedokun 2004; and van der Veen 2011). Donor interest in a recipient might be greater when a recipient is a major trading partner, or lower if a recipient has little geostrategic value. Donor goals might be common if they care more about addressing recipient poverty, or rival if they seek diplomatic influence.

The below section introduces the two-by-two model. Though a two-donor, two-recipient world is certainty far from realistic, it is simple enough to keep the analysis tractable, while being minimally sufficient for conferring lessons about strategic donor actions.[4]

3.1 The Two-by-Two Model

Suppose we have two donor countries, i and j, and two recipient countries, x and y. Each of the donors is endowed with a certain relative share of resources available for allocating aid. Resources possessed by i are denoted $R_i \in (0, 1)$, and resources possessed by j are given as $R_j = 1 - R_i$. R_i thus denotes the distribution of resources between i and j.

As i and j distribute resources in the form of aid to x and y, they each are able to realize certain baskets of foreign policy objectives through their allocations. $X \subseteq \mathbb{R}_+$ represents this basket of objectives with respect to recipient x, and $Y \subseteq \mathbb{R}_+$ represents this basket of objectives with respect to recipient y. Further, the quantity $X_i \in X$ denotes how much of i's total foreign policy objectives are realized by giving aid to recipient x, while the quantity $Y_i \in Y$ denotes how much of i's total foreign policy objectives are realized by giving aid to recipient y. Similar quantities exist for donor j.

As i and j allot resources between x and y, let the objectives donors are able to realize be linear functions of the amount of aid they contribute. For example, the basket of goals that i is able to realize through its aid allocations to each recipient are given as

$$X_i = x_i + \eta^x x_j \quad \text{and} \quad Y_i = y_i + \eta^y y_j, \tag{1}$$

where X poses no externality on Y, and vice versa. For each set of goals, the values x_i and y_i denote i's contribution of aid, while x_j and y_j denote j's. These quantities are strictly non-negative and bound such that $x_i + y_i \leqslant R_i$, and similarly for j. This means that i and j cannot spend more than their total endowment of resources in giving aid to both x and y.

While the effect of i's aid in support of its own goals is assumed to be constant, the effect of aid contributed by j is conditional on the net externality that j's aid poses to i's

[4] Though, of course, we might observe some interesting and novel behavior in a three-by-two model as well.

overall objectives. The externality of j's aid is represented by the terms $\eta^x, \eta^y \in (-1,1)$. These reflect the extent to which the basket of foreign policy objectives donors realize through giving aid to each recipient are either on net rival or common. For example, if $-1 < \eta^x < 0$, then j's foreign aid to x overall subtracts from i's ability to realize the sum of its goals in giving aid to this recipient. Conversely, if $0 < \eta^x < 1$, then j's foreign aid overall helps i to realize the sum of its goals in giving aid to x. In the case that $\eta^x = 0$, the net impact of j's aid is zero.

Assuming donors have well-behaved and monotonically increasing preferences over objectives they realize through giving aid to x and y, utility for each can be represented by a function $u(\cdot)$ that is strictly increasing in quantities X and Y, is at least twice differntiable, and is quasi-concave. To keep the math simple, a convenient choice that retains these generic properties is Cobb-Douglas. Specifically, utility for i (and similarly for j) can be represented as

$$u_i(X_i, Y_i) = \sigma_i^x \log(X_i) + \sigma_i^y \log(Y_i). \tag{2}$$

In the above, σ_i^x and σ_i^y capture returns to scale for the sum of objectives i is able to realize with respect to recipients x and y. These are such that $\sigma_i^x \in (0,1)$ and $\sigma_i^y = 1 - \sigma_i^x$. These thus represent the relative salience i attaches to realizing certain bundles of objectives with respect to recipient countries. As $\sigma_i^x \to 1$, i places greater weight on realizing its goals by giving aid to x than it does in giving aid to y.

Assuming i and j are rational, self-interested actors, each will distribute aid between recipients in such a way that maximizes its own utility. Assuming an interior solution, this implies that for i, it will distribute its resources between x and y such that[5]

$$\frac{\sigma_i^x}{x_i + \eta^x x_j} = \frac{\sigma_i^y}{y_i + \eta^y y_j}. \tag{3}$$

[5] Under a fixed resource constraint, i's utility is maximized when $\partial u_i / \partial x_i = \partial u_i / \partial y_i$. $\partial u_i / \partial x_i = \sigma_i^x / (x_i + \eta^x x_j)$ and $\partial u_i / \partial y_i = \sigma_i^y / (y_i + \eta^y y_j)$

Table 1: A Typology of Strategic Relationships

Adversaries	*Competitors*	*Friends*
$\eta^x, \eta^y < 0$	$\eta^x < 0 \wedge \eta^y > 0$	$\eta^x, \eta^y > 0$
	$\eta^x > 0 \wedge \eta^y < 0$	

The left-hand side of the above equality denotes the marginal utility of aid to x (MU_i^x), and the right-hand side denotes the marginal utility of aid to y (MU_i^y). How i allocates its aid in order to realize its ideal bundle of objectives over recipients will of course depend, not only on its prioritization of recipients, but also on the amount of aid contributed by j between recipients and the externality j's aid represents.

3.2 Friends, Adversaries, and Competitors

Donor i's incentives with respect to j's aid can be summarized according to three general sets of strategic relationships between donors—call these *friends*, *adversaries*, and *competitors*. A summary is given in Table 1.

Suppose, first, that i and j's objectives in giving aid to both x and y are overall mutually beneficial in nature. Hence, $\eta^x, \eta^y > 0$, or, in words, i and j are *friends*. If j were to make some positive transfer of resources $\Delta > 0$ from recipient y to recipient x, the resulting change in i's marginal utilities will be such that

$$\frac{\partial MU_i^x}{\partial \Delta} < 0 \quad \text{and} \quad \frac{\partial MU_i^y}{\partial \Delta} > 0. \tag{4}$$

In words, j's hypothetical transfer of aid to x from y reduces the marginal utility of aid to x, and increases the marginal utility of aid to y. Donor i, in this scenario, has an incentive to give more aid where j gives less. This response is called "strategic substitution." It might also be called strategic deference.[6]

Alternatively, suppose that donors i and j receive on net rival benefits from giving aid

[6]The term free-riding could also apply, though strategic substitution could also just reflect an incentive to specialize in the recipient donor i cares most about.

to both x and y. That is, suppose that they are *adversaries*. Given a similar transfer Δ in the aid j gives to x from y, donor i's marginal utilities will now be such that

$$\frac{\partial MU_i^x}{\partial \Delta} > 0 \quad \text{and} \quad \frac{\partial MU_i^y}{\partial \Delta} < 0. \tag{5}$$

In short, j's transfer increases the marginal utility of aid to x, and decreases the marginal utility of aid to y. Given the hindrance j's aid poses to i, i has an incentive to give more aid where j gives more. This response is called "strategic complementarity," or just competition.

For the third scenario, i and j are rivals with respect to one recipient, but have common goals with respect to the other. In this case, they are *competitors*—a term that conveys a slightly less tense relationship than implied by *adversaries*, but not quite so copacetic as *friends*. Say, for instance, that $\eta^x > 0$ and $\eta^y < 0$. Some transfer Δ now is such that

$$\frac{\partial MU_i^x}{\partial \Delta} < 0 \quad \text{and} \quad \frac{\partial MU_i^y}{\partial \Delta} < 0. \tag{6}$$

That is, j's transfer of aid from y to x both reduces the marginal utility of aid to x, and reduces the marginal utility of aid to y. Donor j's aid overall contributes to the realization of i's goals in giving aid to x, giving i an incentive to reduce its own aid to x. However, at the same time, by j transferring aid away from y to x, i also has an incentive to reduce the aid it gives to y. Donor i no longer has to give as much aid to y in order to realize the sum of its objectives in giving aid to that recipient, thus freeing resources that it can give to recipient x.

What will donor i ultimately choose to do? The answer to this question hinges on i's priorities and the relative magnitude of the positive and negative externalities j's aid poses between recipients. These parameters will determine whether the rate at which the transfer Δ reduces the marginal utility of aid to x is greater than, equal to, or less than the transfer's effect on the marginal utility of aid to y. If, for example,

$$\frac{\partial^2 MU_i^x}{\partial \Delta^2} > \frac{\partial^2 MU_i^y}{\partial \Delta^2} \tag{7}$$

then as a result of the transfer, i's overall incentive will be to give more aid where j gives more aid. That is, i will seize the opportunity to compete less over rival gains with respect to recipient y to realize more of its goals in giving aid to x. In short, it will respond with strategic complementarity. Conversely, if

$$\frac{\partial^2 MU_i^x}{\partial \Delta^2} < \frac{\partial^2 MU_i^y}{\partial \Delta^2} \tag{8}$$

then i's incentive will be to give less aid where j gives more. In short, i will take advantage of the greater aid j gives to recipient x to realize more of its rival objectives in giving aid to y. That is, it will respond with strategic substitution.

In summary, the possible values of the externality parameters can be organized according to three types of strategic relationships between countries: (1) *friends*, (2) *adversaries*, and (3) *competitors*. The first and second categories denote contexts where i and j either receive net mutual benefits through their aid allocations across all recipients, or net rival benefits. The last category denotes the case where states have a mix of rival and common goals where rival goals are predominantly realized in giving aid to one recipient, and common goals are predominantly realized in giving aid to the other. Much of the analysis that follows—especially equilibrium analysis and comparative statics—will home in on the competitors case given the greater likelihood of donors being competitors "in the wild." However, to illustrate the breadth of incentives that may arise in the model, the next section gives equal attention to all three.

3.3 Deriving Best Responses

The above reveals some important dynamics in donor incentives vis-à-vis one another. However, it does not provide enough to yield specific predictions. To do this, it will be necessarily to explicitly derive actors' best-response functions.

The first step is to specify each donor's utility maximization problem. For i this is given as:

$$\max_{x_i, y_i \in \mathbb{R}^2_+} u_i(x_i + \eta^x x_j, y_i + \eta^y y_j), \quad \text{subject to:} \quad x_i + y_i \leqslant R_i \text{ and } x_i, y_i \geqslant 0. \tag{9}$$

From this, because we have an optimization problem subject to inequality constraints, we form the following Lagrangian:

$$\mathcal{L}_i = u(x_i + \eta^x x_j, y_i + \eta^y y_j) + \lambda^R(R_i - x_i - y_i) + \lambda^x x_i + \lambda^y y_i, \tag{10}$$

where the Karush-Kuhn-Tucker (KKT) necessary conditions for a vector of maximizers (x_i^*, y_i^*) are

$$\begin{aligned} &\frac{\partial \mathcal{L}_i}{\partial x_i} \geqslant 0 \quad x_i \geqslant 0 \quad \lambda^x \geqslant 0 \quad \lambda^x x_i = 0, \\ &\frac{\partial \mathcal{L}_i}{\partial y_i} \geqslant 0 \quad y_i \geqslant 0 \quad \lambda^y \geqslant 0 \quad \lambda^y y_i = 0, \\ &R_i - x_i - y_i \geqslant 0 \quad \lambda^R \geqslant 0 \quad \lambda^R(R_i - x_i - y_i) = 0. \end{aligned} \tag{11}$$

These are the complementary slackness conditions. For objective bundle X, the above implies that either $\lambda^x = 0$ and $x_i > 0$, or $\lambda^x > 0$ and $x_i = 0$. This is similarly true for λ^y and y_i, and λ^R and $R_i - x_i - y_i$. Given that utility is monotonically increasing, we may assume $\lambda^R > 0$ and that i expends all of its available resources in giving aid to x and y.

From the above, we derive the following solution for a system of best response equations for i:

$$
\begin{aligned}
x_i^* &= \sigma_i^x \left(R_i + \eta^x x_j + \eta^y y_j\right) - \eta^x x_j, \\
y_i^* &= \sigma_i^y \left(R_i + \eta^x x_j + \eta^y y_j\right) - \eta^y y_j.
\end{aligned}
\tag{12}
$$

This solution holds assuming an interior solution, but it is certainly possible that states could specialize in one or the other aid recipient entirely. In such cases, it is necessary to be a little more explicit about the above equations. To ensure that corner solutions really stay bound at the corners, the best response functions will explicitly be such that $x_i^* = \min\{\max\{\cdot, 0\}, R_i\}$. This form ensures that $0 \leqslant x_i^* \leqslant R_i$. However, using the implicit functional form is notationally convenient.

We can further simplify the analysis by reducing best-responses to a single objective. This follows naturally from Walras's Law, which in this particular context implies that $\sum_i \left(x_i^* + y_i^* - R_i\right) = 0$. In words, because global resources will equal total demand, it is possible to represent i's best response with respect to only a single recipient, since an equilibrium with respect to one necessarily implies an equilibrium with respect to the other. Simplifying for the best-response with respect to X for example yields:

$$x_i^* = \delta_0 + \delta_1 R_i + \delta_2 x_j, \tag{13}$$

with the following identities for the intercept and slope parameters:

$$\delta_0 := \sigma_i^x \eta^y, \quad \delta_1 := \sigma_i^x - \sigma_i^x \eta^y, \quad \delta_2 := \sigma_i^x (\eta^x - \eta^y) - \eta^x. \tag{14}$$

By definition, this then implies that i's optimal provision of aid to y is simply

$$y_i^* = R_i - x_i^* = (1 - \delta_1) R_i - \delta_0 - \delta_2 x_j. \tag{15}$$

By being able to express best-responses as a simple function of donors' activity with respect to a single recipient, this makes the identification of equilibrium aid allocations all the easier.

3.4 Some Informative Cases

Before identifying equilibria and their welfare implications, it will be helpful to illustrate some examples of best responses, if only to provide further intuition about the incentives donors face in allotting foreign aid in service of their foreign policy goals. The below examples walk through the three general cases highlighted previously: *friends*, *adversaries*, and *competitors*.

3.4.1 Case 1: Friends

As a first case, consider a world where states' strategic relationship is that of *friends*. That is, donors i and j pursue mutually beneficial sets of objectives in giving aid to x and y: $\eta^x, \eta^y > 0$. In this case, each donor's best response to the aid allocated by the other will be strategic substitution—to give less aid where the other gives more. For donor i, this implies that for its best-response equation,

$$x_i^* = \delta_0 + \delta_1 R_i + \delta_2 x_j, \tag{16}$$

the parameter $\delta_2 < 0$.

Figure 1 shows some possible reaction paths. The left panel shows i's aid allocations to x, and the right panel shows i's aid allocations to y. Red denotes an instance where i gives more weight to its foreign policy goals with respect to recipient y ($\sigma_i^x = 1/4$). The blue line denotes an alternative example where i gives more weight to its goals with respect to x ($\sigma_i^x = 3/4$). In both cases the externality parameters are such that $\eta^x = 3/4$ and $\eta^y = 1/2$.

Recall from the identity of δ_2 that its magnitude and direction will be a function of i's preference for recipient x, and the externalities of j's aid to both x and to y. In each set

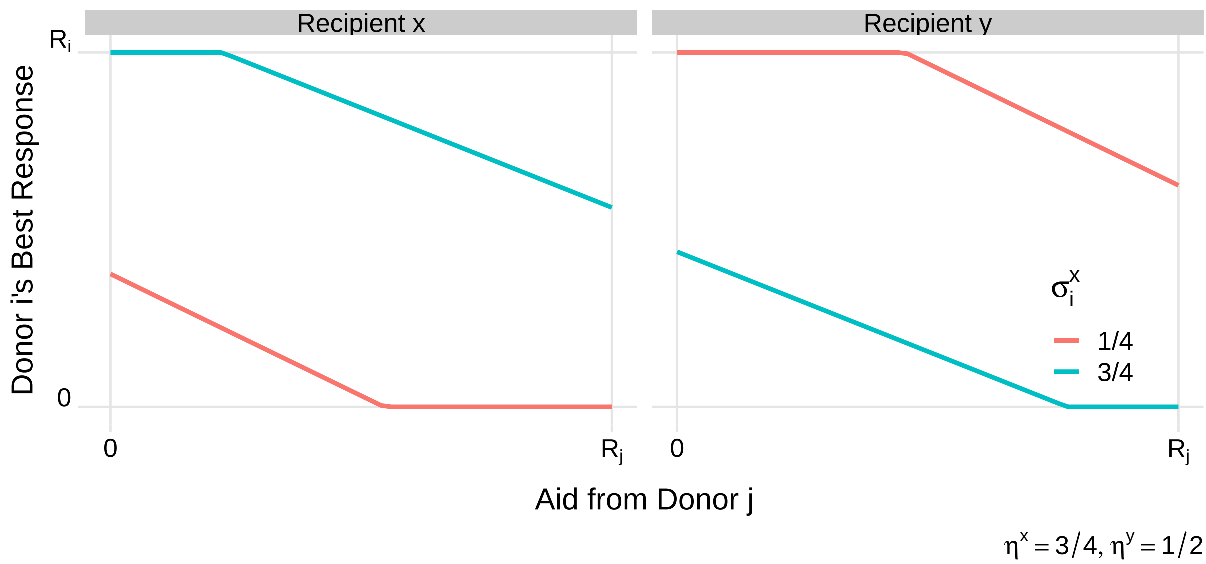

Figure 1: Case 1 reaction paths for donor i in response to j's aid allocations.

of examples, country i's best-response is substitution; though in the former case, i gives less aid overall to x and will defer all responsibility for giving aid to x if j's allocation is sufficiently large. However, in the latter case, where i cares more about x than y, the slope of the reaction is slightly attenuated. Also, due to the higher weight i attaches to giving aid to x, i's incentives are such that, if j gives sufficiently little aid to x, it will entirely defer responsibility for giving aid to y onto j and will give aid exclusively to x.

The emergence of corner solutions is also a function of R_i. If i's share of resources is much less than j's, it is far more likely that i has a corner solution for one of the recipients. The greater R_j relative to R_i, the farther right along the x-axis j's potential contribution of aid may go—and thus, the more likely i's best response path meets with zero. The real-world prevalence of corner solutions among smaller aid donors illustrates the implications of this quite well. Given their more limited resources, to the extent that donors have common objects with respect to at least some recipients, smaller donors like Iceland, the Netherlands, and Greece should have a greater number of corner solutions than larger

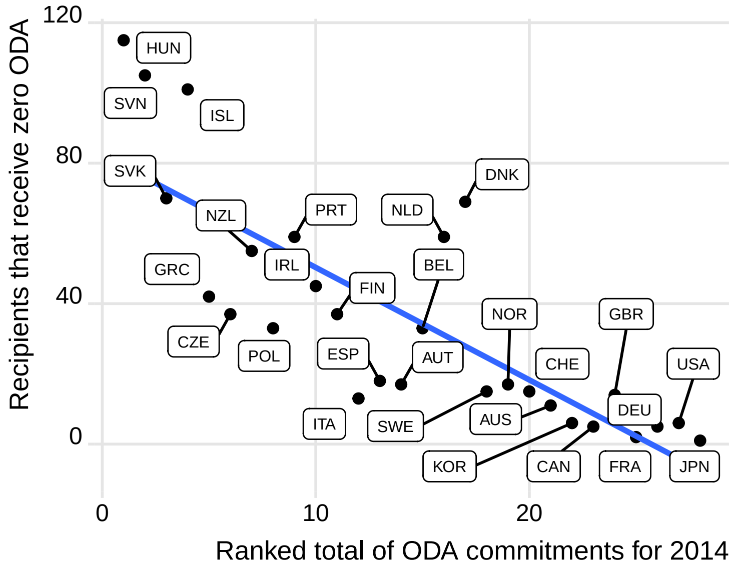

Figure 2: Smaller donors have a greater number of corner solutions. Example with ODA data from 2014.

donors like the U.S., Japan, and the U.K. This much is evident from Figure 2.[7] Along the x-axis the ranked total ODA expenditures of donors in 2014 across 24 key development sectors are shown. Along the y-axis the number of recipients that received zero dollars in aid across these 24 sectors from a given donor are shown. A clear relationship between total aid expenditures and the prevalence of corner solutions emerges. The top 5 donors for 2014 are Japan, the U.S., Germany, France, and the U.K. The number of recipients in the data that receive zero aid across the 24 development sectors from each donor is 1, 6, 5, 2, and 14 respectively. Meanwhile, the bottom 5 donors—Hungary, Slovenia, Slovakia, Iceland, and Greece—have 115, 105, 70, 101, and 42 recipients that receive zero aid across these same sectors.

3.4.2 Case 2: Adversaries

Consider an alternative case where i and j are *adversaries*. That is, $\eta^x, \eta^y < 0$. In this case, whatever the arrangement of i's preferences, its best response to j will always be strategic complementarity: e.g., $\delta_2 > 0$.

[7]ODA data comes from *OECD.stat*.

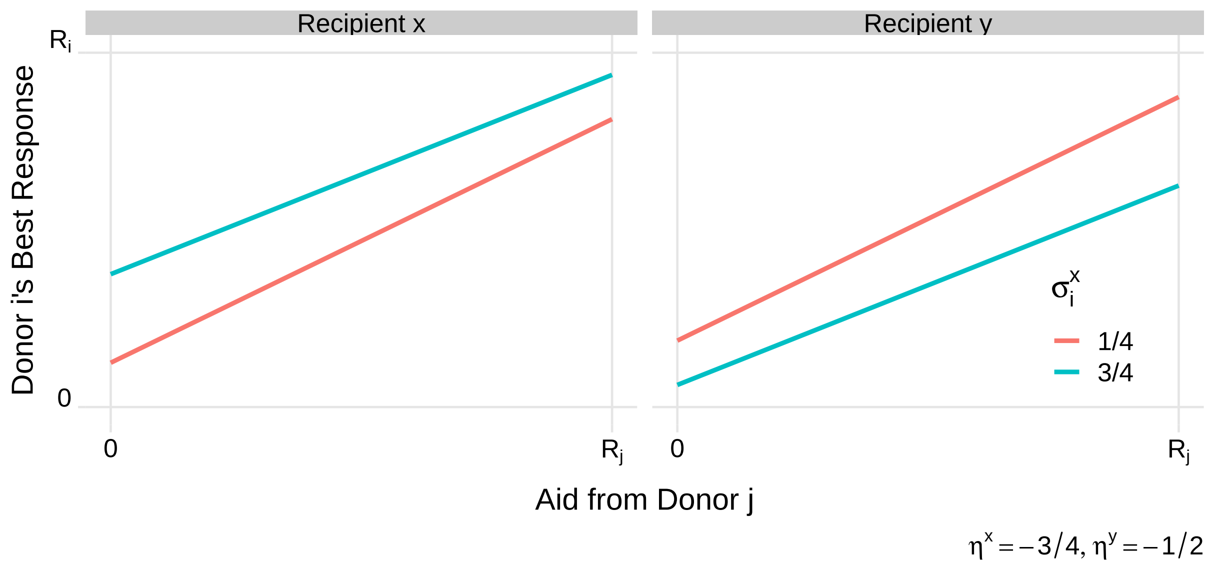

Figure 3: Case 2 reaction paths for donor i in response to j's aid allocations.

Figure 3 shows a set of examples similar to those given in Figure 1. The main difference, of course, is that the externalities posed by j's aid are now negative: $\eta^x = -3/4$ and $\eta^y = -1/2$. The red slope shows i's best response if it cared more about recipient y than x ($\sigma_i^x = 1/4$), and the blue slope shows i's best response if it cared more about recipient x than y ($\sigma_i^x = 3/4$). i's response is slightly attenuated in the second case, while its level of aid allocation to x (y) is overall greater (lower).

An appropriate analogue for this scenario is an arms race. As Glaser (2000) states regarding arms races, the prevailing view sees arms buildups as the product of a cycle of "action" and "reaction" where states expand their armaments in an effort to shore up their own security in the face of an adversary. In a similar way, aid donors that are adversaries respond to each other by targeting greater and greater shares of their aid where their opponent targets more of theirs in order to maintain their foreign policy interests.

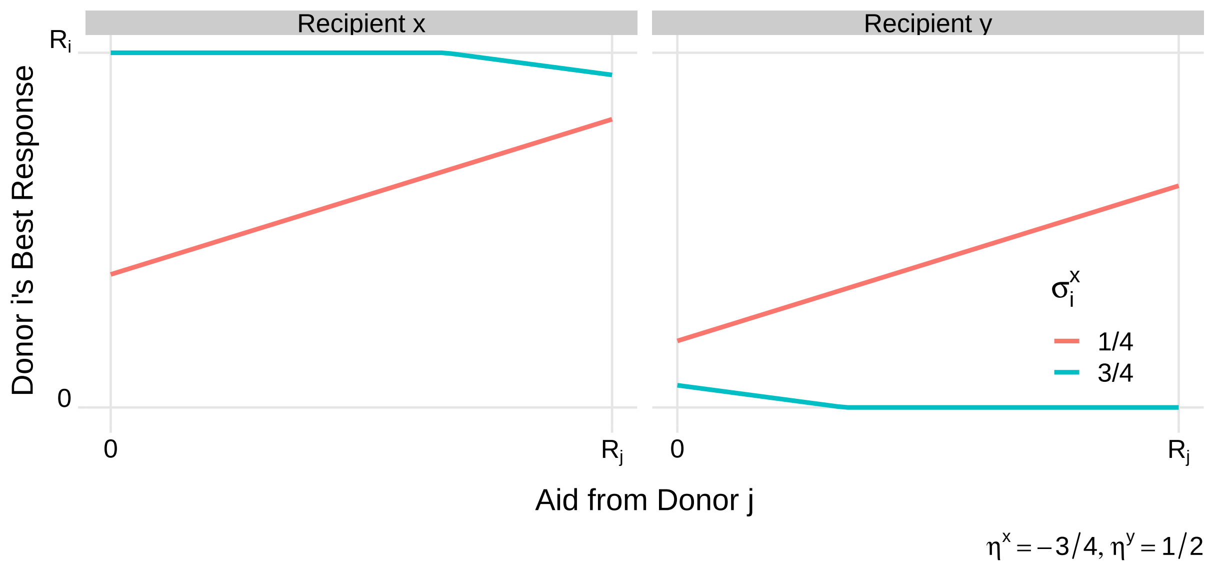

Figure 4: Case 3 reaction paths for donor i in response to j's aid allocations.

3.4.3 Case 3: Competitors

Now, consider the third scenario where i and j are *competitors*. Suppose that while i and j pursue on net rival objectives in giving aid to x, they have predominantly common objectives in giving aid to y. In this particular case, the sign of i's reaction to j may be either positive or negative. Which emerges will hinge on variation in the externality parameters and the weight i attaches to its goals in giving aid to recipients.

Figure 4 illustrates this point. The red line denotes a case where i cares more about its goals in giving aid to y than to x ($\sigma_i^x = 1/4$). In this instance, i's best strategic response to j's aid allocation is strategic complementarity. Alternatively, in the case where i cares more about x than y, the blue line, i's best response is strategic substitution. What accounts for this difference?

As it turns out, i's priorities over recipients plays a key role in conditioning its response to j. In the first example, i cares relatively little about recipient x, which means the competitive threat posed by j giving aid to x dominates its response. This can be seen by considering the identity of δ_2:

$$\delta_2 = \sigma_i^x(\eta^x - \eta^y) - \eta^x. \tag{17}$$

As σ_i^x approaches zero, the sign and magnitude of η^x becomes increasingly determinant of how i responds to j's aid to x. In fact, it is the case that

$$\sigma_i^x \to 0 \quad \Longrightarrow \quad \sigma_i^x(\eta^x - \eta^y) - \eta^x \to -\eta^x. \tag{18}$$

In words, absent substantial intrinsic interest in realizing certain goals by giving aid to a recipient country, the externality created by other-donor aid becomes the primary factor determining aid allocation.

A well-known real-world case of such a strategic dynamic can be seen in how Western countries dramatically cut aid to various authoritarian regimes after the collapse of the Soviet Union (Bräutigam and Knack 2004). With the negative externality posed by Soviet aid gone, Western donors had little remaining incentive to continue to give aid to recipients that had little intrinsic value absent a geostrategic rival.

A similar logic explains why there is a shift in i's strategic response from complementarity to substitution given a sufficient shift in the salience it attaches to recipients. This is seen by observing what happens to the slope of i's reaction in the limit where σ_i^x approaches one:

$$\sigma_i^x \to 1 \quad \Longrightarrow \quad \sigma_i^x(\eta^x - \eta^y) - \eta^x \to -\eta^y. \tag{19}$$

In words, the more i cares about recipient x, the more the externality created by j's aid to y shapes its strategic response. In the example shown in Figure 4, i's interest in recipient x is great enough (and hence its interest in y low enough) that its strategic behavior is most determined by the positive impact of j's aid to y. In short, this means that the more aid j

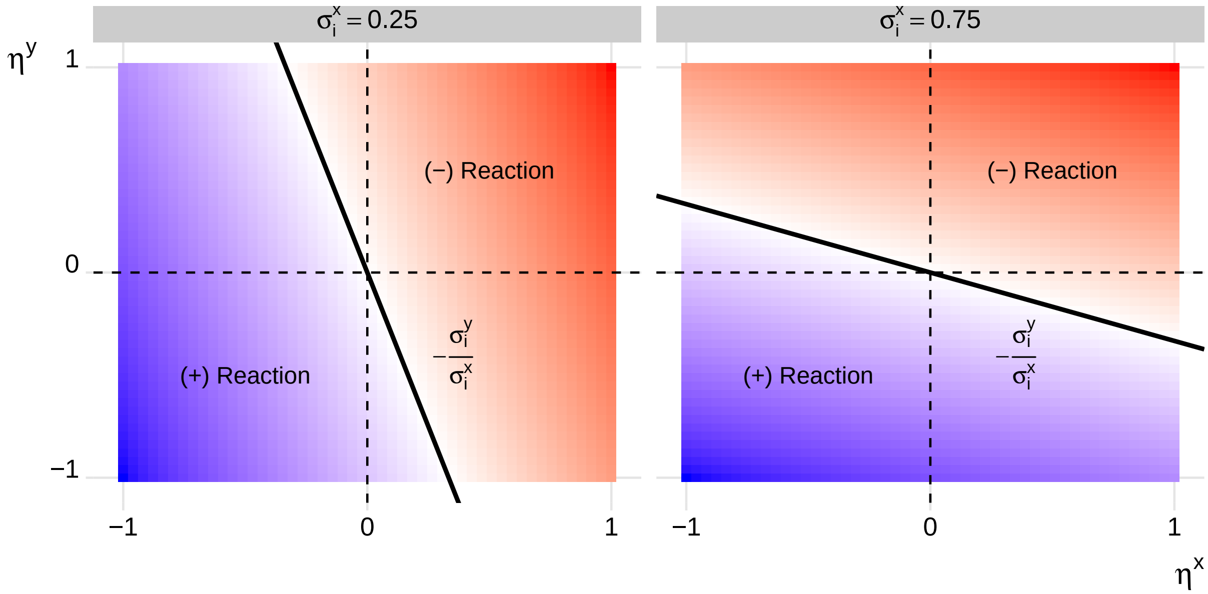

Figure 5: Possible directions of reaction paths.

gives to y, the more i takes advantage of j's giving to direct its resources toward realizing its goals in giving aid to x.

3.5 A Summary of Cases

The above cases reveal how variation in externalities and country priorities over foreign policy objectives can lead to a variety of best responses. It would be impossible to describe every possible scenario; however, it is possible to describe the range of best responses given arrangements of externality parameters and preferences. Figure 5 offers such a summary.

The left panel shows the range of best responses i might have to j's aid over the range of possible values of the externality parameters. For this particular example, i's preferences between recipients are held constant at $\sigma_i^x = 1/4$. The right panel shows the range of best responses i might have to j's aid over the same range of possible values of the externality parameters. In this case, i's preferences between recipients are held constant at $\sigma_j^x = 3/4$.

The blue areas denote instances where a i's best response is strategic complementarity, or a positive reaction to where the other donor gives aid. The red areas denote instances where i's best response is strategic substitution, or a negative reaction to where the other donor gives aid. The relative lightness of the colors captures the magnitude of the strategic response—as the shade darkens, the response becomes more severe, while as the shade lightens, the response approaches zero.

Consistent with the three preceding cases, this summary aligns with the three-part typology of strategic relationships between countries i and j suggested earlier—e.g., that countries' strategic relationship may be that of *friends*, *adversaries*, or *competitors*. Recall that in cases where actors are *friends*, both actors mutually benefit from giving aid to x and y. They consequently have negatively sloped reaction paths, regardless of their preferences, for all possible values of $\eta^x, \eta^y > 0$. Meanwhile, in cases where i and j are *adversaries*, both actors are rivals with respect to x and y. Here, they have positively sloped reaction paths, no matter their preferences, for all $\eta^x, \eta^y < 0$. In both cases, the absolute magnitude of the best-responses will vary depending on the precise parameter values, but the general direction of the responses will not.

However, in cases where i and j are *competitors*—that is, when donors reap mutual benefits with respect to one recipient, and rival benefits with respect to the other—reaction paths may be either positive or negative. The key factor determining which is the case is the relative weight donors place on realizing their foreign policy goals by giving aid to either x or y. As it so happens, the slope of the boundary between negative and positive reactions is equivalent to:

$$-\frac{\sigma_i^y}{\sigma_i^x} \equiv \frac{\sigma_i^x - 1}{\sigma_i^x}. \tag{20}$$

The slope of this line for donor i is shown in black. As $\sigma_i^x \to 1$, the slope approaches zero, while as $\sigma_i^x \to 0$ the slope approaches $-\infty$.

4 Analysis

With the best-responses for actors i and j defined, it is now possible to consider equilibrium distributions of aid, comparative statics, and welfare analysis. Up to now, description of the model has included the breadth of strategic relationships between donor governments. However, in the real-world, certain strategic relationships are more probable than others. Specifically, while the model allows for donors to be pure *friends* or *adversaries*, in terms of the parameter space donors are more likely to be *competitors*—having a mix of rival and common interests. Such a strategic dynamic is also most realistic for leading donor governments. Industrialized countries distribute aid across more than a hundred recipients. While donor interests with respect to some of these recipients may be rival, there may be several instances where donor interests are common. To narrow the focus to cases that may be most relevant for thinking about the strategic incentives of prominent donors, I will restrict the analysis to cases where $\eta_x < 0$ and $\eta_y > 0$.

To support this exercise, of course, it will be necessary to first know with certainty that the equilibria to be analyzed exist, are unique, and are well-behaved. If equilibrium solutions do not exist, then it would make little sense to engage in equilibrium analysis. And, if said equilibria were not unique, then this would add a great deal of complexity to the analysis, and make identifying equilibrium solutions numerically unfeasible. Further, if said equilibria were not stable, or smooth with respect to the model parameters, comparative statics would prove a dangerous exercise indeed.

Thankfully, it can be shown that

Proposition 4.1 *There always exists a **unique** Nash equilibrium vector of best responses* (x_i^*, x_j^*).

See Appendix for proof. ∎

Further, it can be shown that

Proposition 4.2 *The Nash equilibria are smooth with respect to model parameters.*

See Appendix for proof. ∎

However, with respect to the first proposition, there are some interesting pathologies that emerge at the bounds of the externality parameters: e.g., as $|\eta^x|, |\eta^y| \to 1$. Specifically, at the bounds, *unique* equilibrium solutions do not necessarily exist. Rather, countries i and j may face a coordination problem with respect to an infinite set of pure-strategy Nash equilibria.[8] Fortunately, given that $\eta^x, \eta^y \in (-1, 1)$ (that is, the externality parameters do not include their boundaries at -1 and 1), such pathological cases do not arise in practice.[9]

4.1 Derivation of Nash Equilibria

Knowing the above, it is possible to derive the unique Nash equilibrium. For country i, this solution with respect to recipient x is given as:

$$
\begin{aligned}
x_i^* &= \delta_{i0} + \delta_{i1} R_i + \delta_{i2} x_j^*, \\
x_i^* &= \delta_{i0} + \delta_{i1} R_i + \delta_{i2}(\delta_{j0} + \delta_{j1} R_j + \delta_{j2} x_i^*), \\
x_i^* - \delta_{i2}\delta_{j2} x_i^* &= \delta_{i0} + \delta_{i1} R_i + \delta_{i2}(\delta_{j0} + \delta_{j1} R_j), \\
x_i^* &= \frac{\delta_{i0} + \delta_{i1} R_i + \delta_{i2}\delta_{j0} + \delta_{i2}\delta_{j1} R_j}{1 - \delta_{i2}\delta_{j2}}.
\end{aligned}
\tag{21}
$$

By symmetry, j's equilibrium allocation to x is

$$
x_j^* = \frac{\delta_{j0} + \delta_{j1} R_j + \delta_{j2}\delta_{i0} + \delta_{j2}\delta_{i1} R_i}{1 - \delta_{i2}\delta_{j2}}. \tag{22}
$$

[8] There are mixed-strategies as well.

[9] This is a nakedly utilitarian reason for specifying the externality parameters as such.

If we replace the δ parameters with their identities, the solution expands to:

$$
\begin{aligned}
x_i^* = \{&\sigma_i^x \eta^y + (\sigma_i^x - \sigma_i^x \eta^y) R_i + \\
&[\sigma_i^x(\eta^x - \eta^y) - \eta^x]\sigma_j^x \eta^y + \\
&[\sigma_i^x(\eta^x - \eta^y) - \eta^x](\sigma_j^x - \sigma_j^x \eta^y) R_j\} / \\
&\quad \{1 - [\sigma_i^x(\eta^x - \eta^y) - \eta^x][\sigma_j^x(\eta^x - \eta^y) - \eta^x]\}
\end{aligned}
\tag{23}
$$

From Walras' Law, an equilibrium with respect to x implies an equilibrium solution for y. Hence, whatever solution we have for x, the equilibrium aid allocations to y for i and j are simply:

$$
y_i^* = R_i - x_i^* \quad \text{and} \quad y_j^* = R_j - x_j^*. \tag{24}
$$

It should be noted that while these functional forms are continuous with respect to the model parameters, the explicit functional form for these solutions is restricted to the bounds $0 \leq x_i^* \leq R_i$.

4.2 Comparative Statics

Variation in model parameters reveals a considerable diversity of possible equilibrium outcomes. In this section, many such possibilities are considered using motivating examples. The goal is not only to demonstrate how predictions shift with model parameters, but also to show that the model yields predictions that it *ought* to make.

Consider, first, an example motivated by a real-world event: the collapse of the Soviet Union as a sizable threat to US foreign policy interests. Telling of how the United States' incentives shifted after the Soviet Union was out of the picture, during the Cold War years, the US gave disproportionately more aid to developing countries bordering communist nations. However, after the Cold War, having a communist neighbor ceased to be a significant predictor of US aid (Meernik, Krueger, and Poe 1998). This change implies

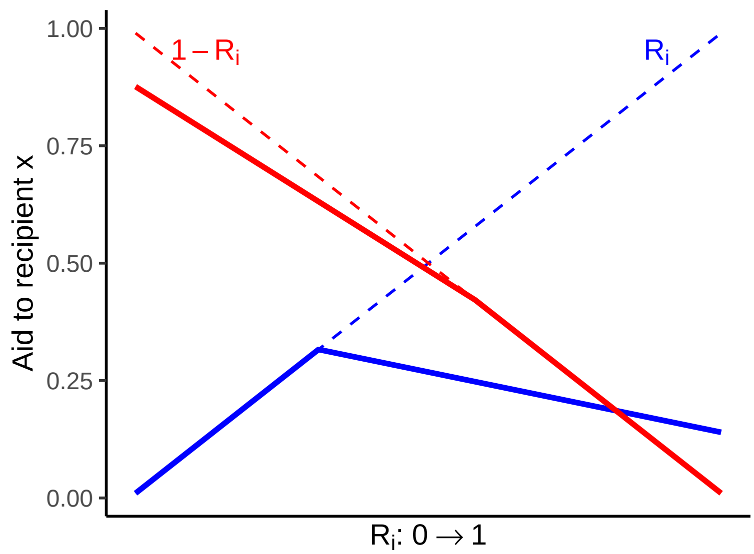

Figure 6: The implications of a diminished foreign aid donor. Donor i is in blue, and donor j is in red. Dashed lines show donors' share of resources. If aid expenditures overlap with these budget lines, donors have a corner solution.

recipients with a communist neighbor were not intrinsically valuable to the US, but were important targets of aid nonetheless due to possible competition from the USSR. With competition no longer active, and little intrinsic value placed on these countries otherwise, they saw a reduction in US aid.

This is precisely what the model predicts would happen, as shown in Figure 6. For this example, the σ and η parameters are held constant at $\sigma_i^x = 1/10$, $\sigma_j^x = 9/10$, $\eta^x = -1/2$, and $\eta^y = 1/10$ respectively. That is, i and j are rivals with respect to recipient x while they obtain common benefits from giving aid to y. In this example, the negative externality posed by aid to x is more substantial than is the positive externality of aid to y. Further, j cares much more about recipient x than y, while i cares much more about y than it does x. From the left to the right of the x-axis, i's share of resources shifts between 0 and 1.

The increase in i's relative resource endowment results in a shift in equilibrium aid allocations consistent with what occurred with the collapse of the Soviet Union. As i's resources compared to j's increase, i's contribution of aid to recipient x declines. This is due to the diminished threat to i's interests with respect to x posed by j.

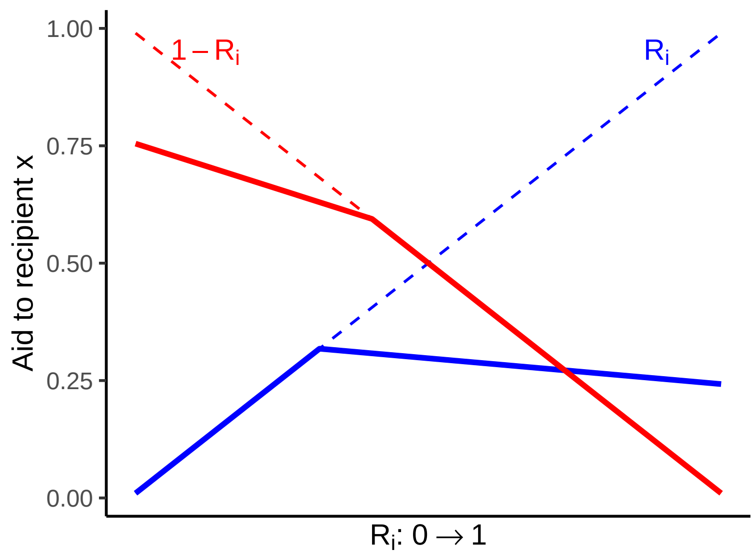

Figure 7: Smaller donors and corner solutions. Donor i is in blue, and donor j is in red. Dashed lines show donors' share of resources. If aid expenditures overlap with these budget lines, donors have a corner solution.

The model yields other predictions that are consistent with well-documented patterns in donor giving. In a previous section, it was noted that governments of smaller donors were more likely to have corner solutions—to give zero aid to at least one recipient. Indeed, the empirical record is consistent with this view. Among *competitors*, corner solutions are likely to emerge as the smaller of the two donors is forced to sacrifice support for common interests in one recipient in order to compete over rival objectives with respect to the other. Holding the parameters at $\sigma_i = 1/10$, $\sigma_j = 9/10$, $\eta^x = -1/2$, and $\eta^y = 1/2$, Figure 7 shows how donors' aid to recipient x change as R_i shifts from between 0 and 1. As the balance of resources shifts from j's to i's favor, i ceases to have a corner solution (to give its entire aid budget to x to compete for rival gains), while j shifts toward having a corner solution.

The model also offers lessons for relatively new developments in aid politics. Consider the rise of China as an important aid donor. A worry among many policymakers is that differences in China's priorities relative to those of Western donors poses a threat to the interests of countries like the United States and Japan. A normative concern among

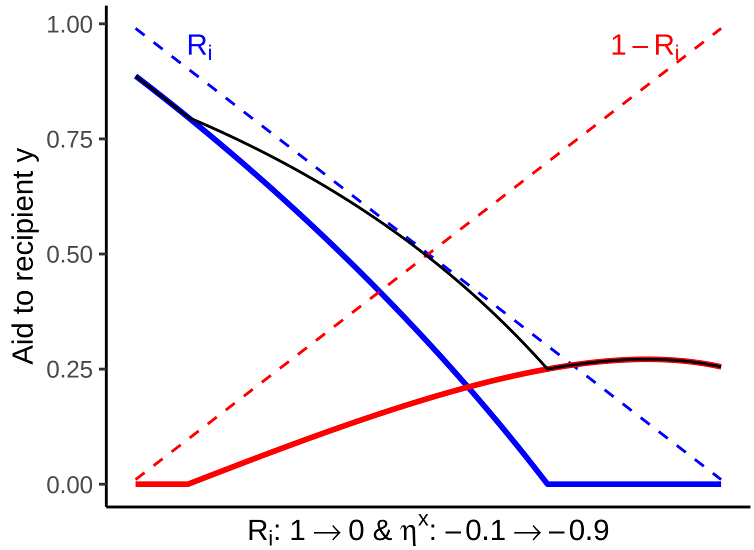

Figure 8: The 'rise' of China. Donor i is in blue, and donor j is in red. Black denotes the sum total of aid to y. Dashed lines show donors' share of resources. If aid expenditures overlap with these budget lines, donors have a corner solution.

researchers is that rivalry with China will alter the way traditional donors target their aid with negative consequences for aid recipients. Several studies have already shown how China's aid practices not only influence where DAC countries target their aid, but also the types of projects they are likely to support (Zeitz 2021).

Such negative consequences are consistent with the model. The rise of a donor that increasingly values promoting its geostrategic and selfish economic interests in targeting aid has unfortunate implications for the global distribution of aid. Consider the example shown in Figure 8, which depicts aid from donors i and j to recipient y—where donors' aid has mutually beneficial effects for both donors. In this instance, as the government of j enjoys an increase in its share of resources, the negative externality of its aid to x worsens. For this particular numerical example, R_i shifts from between 1 to 0 (moving in j's favor), while η^x shifts from -0.1 to -0.9 (meaning rivalry in x worsens).

The equilibrium behavior of both donor governments is consistent with many analysts' and policymakers' worst fears. Aid to recipient y, which is a site of mutual interests between i and j, receives not only less support from i as the balance of resources moves toward j's favor, it also receives less total aid over all, denoted by the solid black line. As it so happens, in this example $\sigma_i^x = 1/10$, meaning that the government of i cares much less about x than it does y. Nonetheless, competitive pressure leads i to eventually forego giving aid to y altogether in an effort to compete with j.

4.3 Welfare Analysis

Among the cases considered above, the last one in particular underlines that as donors seek to maximize their own foreign policy interests, their individual best-responses may lead them to distribute aid in ways that are collectively inefficient.[10] The (in)efficiency of the equilibrium solutions the model predicts can be evaluated by comparing the sum of actors' utilities under Nash behavior relative to the sum of their utilities under some alternative maximizing principal, say:

$$\max_{x_i, x_j, y_i, y_j \in [0,1]} u_i(X_i, Y_i) + u_j(X_j, Y_j), \tag{25}$$

subject to

$$x_i + x_j + y_i + y_j \leq R_i + R_j = 1. \tag{26}$$

In this formulation, the objective is to maximize the combined utility of donors i and j by finding the optimal distribution of their combined aid budgets. This can be done by forming the Lagrangian

$$\begin{aligned} \mathcal{L} = {} & u_i(x_i + \eta^x x_j, y_i + \eta^y y_j) + u_j(x_j + \eta^x x_i, y_j + \eta^y y_i) \\ & + \lambda^R(1 - x_i - y_i - x_j - y_j) + \lambda_i^x x_i + \lambda_i^y y_i + \lambda_j^x x_j + \lambda_j^y y_j, \end{aligned} \tag{27}$$

[10] I use *Pareto* interchangeably with *collectively*.

with KKT conditions:

$$
\begin{aligned}
&\frac{\partial \mathcal{L}}{\partial x_i} \geqslant 0 \quad x_i \geqslant 0 \quad \lambda_i^x \geqslant 0 \quad \lambda^x x_i = 0, \\
&\frac{\partial \mathcal{L}}{\partial y_i} \geqslant 0 \quad y_i \geqslant 0 \quad \lambda_i^y \geqslant 0 \quad \lambda^y y_i = 0, \\
&\frac{\partial \mathcal{L}}{\partial x_j} \geqslant 0 \quad x_j \geqslant 0 \quad \lambda_j^x \geqslant 0 \quad \lambda^x x_i = 0, \\
&\frac{\partial \mathcal{L}}{\partial y_j} \geqslant 0 \quad y_j \geqslant 0 \quad \lambda_i^y \geqslant 0 \quad \lambda^y y_i = 0, \\
&1 - x_i - y_i - x_j - y_j \geqslant 0 \quad \lambda^R \geqslant 0 \quad \lambda^R(1 - x_i - y_i - x_j - y_j) = 0.
\end{aligned}
\tag{28}
$$

Since, like the individual optimization problem, this collective optimization problem is concave, we are assured the existence of a unique vector of maximizers $(x_i^o, x_j^o, y_i^o, y_j^o)$.[11] This solution is Pareto optimal if this vector yields greater payoffs for *at least one* of the actors, and leaves the other at least as well off relative to alternatives.

This solution is, by definition, Pareto optimal. However, many solutions in a given game may be Pareto optimal. For the welfare analysis, we are most interested in knowing whether an efficient collective solution Pareto improves on a Nash equilibrium solution. The condition for this is:

$$
u_k^o \geqslant u_k^n \quad \forall \quad k \in \{i, j\} \quad \wedge \quad u_m^o > u_m^n \quad \text{for at least one } m \in \{i, j\} \tag{29}
$$

where the o superscript denotes utility for donors when collective utility is maximized, and the n superscript denotes utility for donors in equilibrium. In words, the collective solution must improve utility for at least one of the donor governments, and at minimum not change utility for the other. If this condition fails to be met, then the Nash solution, in addition to the collective solution, is Pareto efficient.

An example of a how i's and j's equilibrium responses fair with respect to collective

[11] Since the returns to scale in the Cobb-Douglas utilities are diminishing, they are concave. Because the collective utility function is the sum of these concave utility functions, it also is concave.

utility is shown in Figure 9. The reaction paths of countries i and j are shown with respect to recipient x (the left panel) and recipient y (the right panel). The blue line denotes i's best response, and the red line denotes j's. The Nash equilibrium solution lies at the intersection of their best responses. The collectively optimal solution is also shown. This point lies at the convergence of the concentric bands shown in the figure. These bands are isoquants denoting collective utility.

For this example, i and j have an equal share of resources ($R_i = 1/2$) and different priorities over recipients, $\sigma_i^x = 3/4$ and $\sigma_j^x = 1/4$. Further, the externalities with respect to recipient x and with respect to recipient y not only differ in magnitude, but direction ($\eta^x = -1/3$ and $\eta^y = 1/4$). Given this arrangement of parameters, the actors have *different* best-responses. While i's reaction path is positive, j's is negative. That is, i gives more aid where j gives more, but j gives more aid where i gives less. In equilibrium, however, despite the different best-responses of the donors, both nonetheless end up giving *more* aid to x and *less* aid to y than is most collectively efficient. This is shown in the left panel of the figure by the fact that the Nash equilibrium lies up and to the right of the collectively optimal solution. Further, in the right panel of the figure, the Nash equilibrium lies down and to the left of the collectively optimal solution.

The equilibrium that emerges in this particular case is intuitive. The actors receive rival foreign policy gains in giving aid to x, and common foreign policy gains in giving aid to y. As a result, their individual best-response is to give more aid to x than is collectively optimal. This leaves less available resources for giving aid to y.

Hence, while this behavior is individually rational, it is collectively inefficient. Both i and j could be made better off if they would mutually transfer some aid from x to y. This more efficient solution, unfortunately, is inconsistent with each donor's interests.

This particular scenario is not the only one that can emerge. The parameter space allows for wide-ranging outcomes—an infinite number in fact. Nonetheless, a grid search can offer a representative taste for how alternative arrangements of donor priorities, foreign

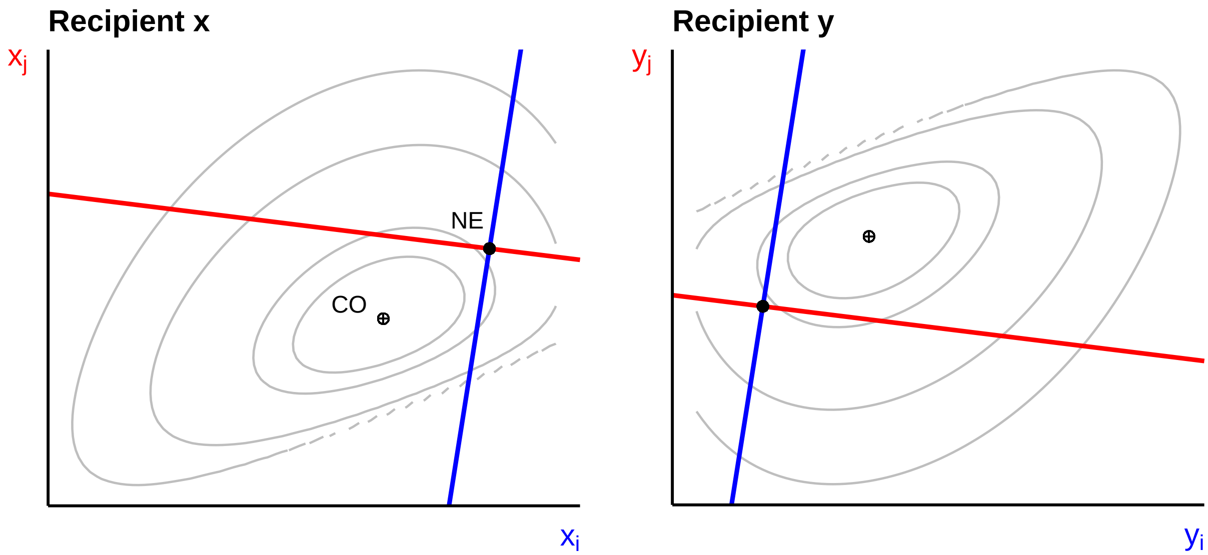

Figure 9: Equilibrium allocations relative to the collective optimum. Results shown for *competitors*. NE = Nash Equilibriu. CO = Collective Optimum. Blue denotes donor i, and Red denotes donor j.

policy externalities, and donor size yield efficient and inefficient outcomes.

Keeping with the focus on studying *competitor* donors, the range of parameters includes all possible combinations of:

- $R_i = (0.1, 0.2, 0.3, ..., 0.9)$;
- $\sigma_i^x = (0.1, 0.2, 0.3, ..., 0.9)$;
- $\sigma_i^y = (0.1, 0.2, 0.3, ..., 0.9)$;
- $\eta^x = (-0.9, -0.8, -0.7, ..., -0.1)$;
- $\eta^y = (0.1, 0.1, 0.3, ..., 0.9)$.

This creates a parameter grid of 59,049 possible combinations to evaluate.

Table 2 summarizes the percentage of examined cases by the suboptimality of the Nash equilibria. In only over 51% of the combinations of parameters explored, the Nash equilibrium solution was inefficient. In nearly 49% of cases, the equilibrium distribution of aid was also Pareto optimal.

Table 2: Inefficiency of Nash Equilibria

Outcomes	Percent
Inefficient	51.37
Conflicting payoffs	48.63
TOTAL	100.00
Suboptimal for both	13.23
Suboptimal for *i or j*	100.00

However, the efficiency of an equilibrium solution does imply that *both* donor governments are better off in equilibrium than under the solution for the collective optimization problem. To the contrary, in many instances, one donor is better off under one and worse under the under—and vice versa.

We can see this by noting that while 51.37% of Nash equilibria are not collectively efficient, 100% of the equilibria leave at least one donor strictly worse off relative to their utility under collective optimization. In fact, in all the remaining 48.63% of cases, which are Pareto optimal, in **all** one donor is strictly better off in equilibrium, while the other is strictly worse off, relative to their payoffs under the solution for collective optimization. In only a mere 13% of equilibria, both donors strictly worse off.

These findings highlight that there is a substantial area of the parameter space where donors will have conflicting preferences between individual and collective optimization. Conversely, there is a much narrower range of parameters where collective optimization yields strong Pareto improvements for donors—that is, where both donors do strictly better relative to their individually best responses.

The inefficient and efficient sets of equilibria vary in interesting ways with respect to donor spending under individual relative to collective optimization. Table 3 summarizes the percentage of inefficient equilibria by whether donors i and j over or under fund aid to x, or whether their spending matches what their collectively efficient supply of aid would be. In 62.5% of cases both i and j gave too much aid to x than is efficient. But, almost 38%

Table 3: Nash Spending Relative to Collective Solution (Inefficient Equilibria)

	i over spends	i under spends	neither
j over spends	62.50	18.55	0.18
j under spends	18.58	0.00	0.00
neither	0.18	0.00	0.00

Table 4: Nash Spending Relative to Collective Solution (Efficient Equilibria)

	i over spends	i under spends	neither
j over spends	71.90	5.79	7.42
j under spends	5.85	0.00	0.80
neither	7.42	0.80	0.00

of the time while one donor over funds aid to x, the other donor gives too little. In no case, however, do both i and j commit too little aid to x in the same equilibrium.

A similar pattern appears in the spending of donors in the set of efficient equilibria. This is shown in Table 4, which summarizes the percentage of efficient equilibria according to donors' spending under individual relative to collective optimization. In 71.9% of cases, donors commit more aid to x in equilibrium than they do under collective optimization. In a much smaller set of cases, while one spends more in equilibrium, the other either spends less or its spending matches its spending under collective optimization. In a narrow 1.6% of cases, while one donor gives less than under collective optimization, the other's spending matches its spending under collective optimization.

While instances of mutual over-spending on aid to x are intuitive—donors have rival interests in x—the cases where one donor either commits too little aid to x, or its spending is equivalent to what its collectively efficient supply of aid would be, are less so. The summary in Table 5 may help to explain what is going on. Cell entries denote the percentage of cases by donor spending among inefficient equilibria where donors have corner solutions (donor j to the left, donor i to the right). The preponderance of cases where one donor either under commits aid, or its aid is equivalent to its efficient level of

Table 5: % Corner Solutions by Nash Spending (Inefficient Equilibria)

	i over spends	i under spends	neither
j over spends	31.91, 31.86	100, 0	0, 100
j under spends	0, 100	NA	NA
neither	100, 0	NA	NA

[a] (Donor j, Donor i)

Table 6: % Corner Solutions by Nash Spending (Efficient Equilibria)

	i over spends	i under spends	neither
j over spends	20.45, 20.38	75.41, 0	0, 100
j under spends	0, 75.43	NA	0, 100
neither	100, 0	100, 0	NA

[a] (Donor j, Donor i)

allocation, involve a corner solution by one (and only ever one) donor. Among cases where j over spends and i under spends on aid to x, donor j has a corner solution (committing all its aid to x) in all cases. Conversely, in all cases where j gives too much aid to x and i's spending matches its efficient supply of aid, j has no corner solutions, while i has only corner solutions. A symmetrical pattern applies to cases where i over spends on aid to x.

A similar pattern applies to efficient equilibria, as shown in Table 6—however, there are some notable differences. For instance, when one donor under spends and the other's matches its spending under collective optimization, the latter has a corner solution in all equilibria. Also, when one donor over spends and the other under spends relative to collective optimization, the former has a corner solution in just over 75% of equilibria. This leaves just under a fourth of cases where donors have an interior solution.

The pattern in corner solutions with respect to the characteristics of donor spending is driven, in no small part, by the distribution of resources between donors. As Figure 10 shows, among the set of inefficient and efficient equilibria, the percentage where i or j have corner solutions increases monotonically with an actor's share of the global aid budget. As the summary in Tables 7 and 8 further indicate, the average distribution of resources

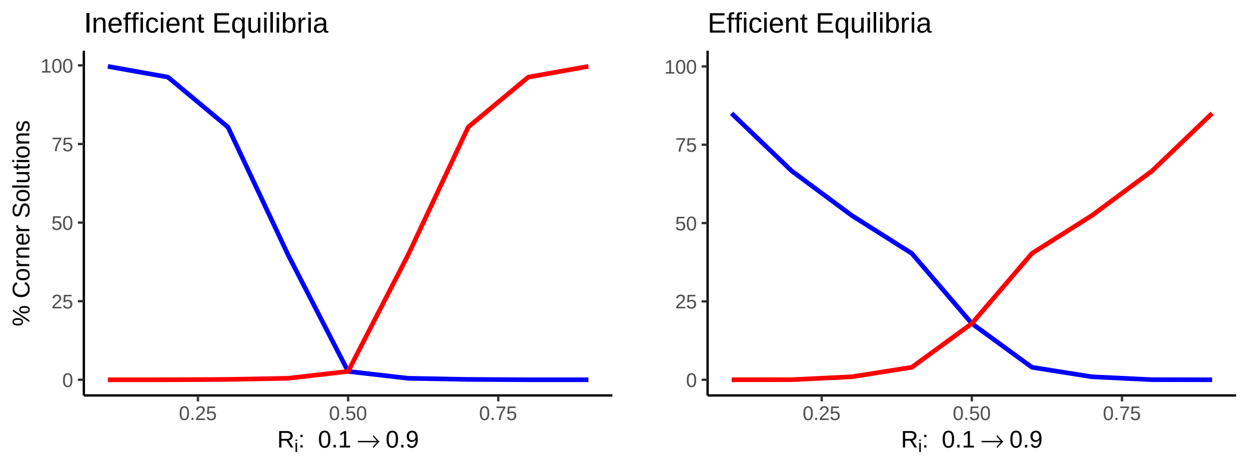

Figure 10: The distribution of resources and the incidence of corner solutions. The percentage of corner solutions for i is in blue. The percentage of corner solutions for j is in red.

Table 7: Distribution of Resources by Spending (Inefficient Equilibria)

	i over spends	i under spends	neither
j over spends	0.50	0.81	0.28
j under spends	0.19	NA	NA
neither	0.72	NA	NA

between actors by their spending characteristics supports the role of R_i in determining over/under funding of aid relative to collective optimization.

One point worth noting about this relationship between R_i, corner solutions, and over/under funding of aid is that it appears that while smaller donor governments have an incentive to support rival foreign policy goals with their aid to the detriment of mutually beneficial goals, larger donors are left to make up for the slack in smaller donor giving to

Table 8: Distribution of Resources by Spending (Efficient Equilibria)

	i over spends	i under spends	neither
j over spends	0.50	0.72	0.28
j under spends	0.28	NA	0.22
neither	0.72	0.78	NA

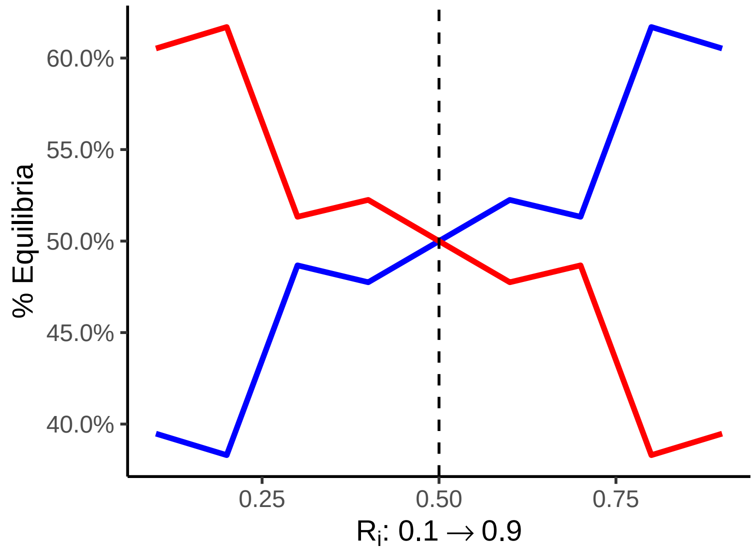

Figure 11: Blue denotes cases where *i* does better under collective optimization, while *j* does worse. Red denotes cases where *j* does better under collective optimization, while *i* does worse. Values denote the percentage of *Pareto efficient* equilibria.

sites of mutual interest. At first blush, this finding may strike some as inconsistent with the empirical record. Many smaller donors—i.e., Nordic countries—have a reputation for greater humanitarian motivation for allocating aid than larger donors such as the United States (Gates and Hoeffler 2004). However, these well-established donor governments may be the exception rather than the rule.[12] Many new and emerging donors—countries that have or are making the transition from aid recipient to aid donor—appear to distribute aid in decidedly less-than-humanitarian ways. These smaller donors tend to focus more on neighboring recipients, show less responsiveness to recipient need, are less likely to target aid away from poorly governed recipients, and respond with fewer resources than traditional donors to natural disasters (Dreher, Nunnenkamp, and Thiele 2011). Emerging donors, then, may be most prone to throw their aid budgets toward realizing rival foreign policy objectives while giving little to no aid when and where it may yield collective benefits for the donor community—consistent with what this model would predict.

[12]In addition these countries would have more corner solutions for a different reason: namely, deference to large donors in recipients where these smaller humanintarian donors care less about development.

Another point worth noting centers on donor payoffs in Pareto efficient equilibria. As already stated, all of the efficient equilibria considered are characterized by conflicting preferences donors have for individual relative to collective optimization. In these cases, the solution under collective optimization, and the Nash equilibrium, are Pareto optimal. However, while one donor does better under one and worse under the other, the opposite is true for the second donor. For instance, if donor i does better in equilibrium, it will be worse off under collective optimization. Conversely, donor j will do better under collective optimization, but will do worse in equilibrium.

Figure 11 shows the percentage of Pareto efficient equilibria over R_i where one donor does better under collective relative to individual optimization. As the results show, smaller donors tend to do better in equilibrium relative to collective optimization. This means smaller donors, more often than not, will have a preference for remaining in equilibrium. Meanwhile, larger donors will more often have a preference for collective optimization. This does not imply that small donors always have an aversion to collective solutions; not does it imply that large donors always prefer them. The range of percentages in Figure 11 is wide, but still far from the 0-100 extremes. Nonetheless, these averages demonstrate that small and larger donors tend have countervailing preferences over individual and collective solutions that are explained by the distribution of resources between actors.

5 Discussion

Despite the illumination cast by a now mammoth body of research, deep understanding of the strategic relationships that exist among donor governments has tended to elude either the grasp or interest of political scientists and economists. Much like Alesina and Dollar (2000) do in their ubiquitously cited "Who Gives Foreign Aid to Whom and Why?" the bulk of studies on this issue emphasize donors' political goals and recipients' needs and policies, leaving a gaping lacuna where donor interests vis-à-vis each other ought to go. Efforts to untangle strategic interactions among donors exist, but none adopt such a general strategic political economy framework as that introduced here.

5.1 What Has this Approach Gotten Us?

With the help of a two-by-two model of aid allocation, the implications of donors pursuing a possibly mixed bag of common and rival objectives through their aid giving was demonstrated. Among the three possible strategic relationships in the model, donors-as-*competitors* is an especially apt analogue for interactions among donor governments. As donors compete to maximize their foreign policy goals through giving aid, they simultaneously have incentives to take advantage of a peer's generosity when they reap common benefits from their aid to one recipient, and incentives to seek advantage in giving aid to a recipient that is a site of rival objectives. In the majority of cases, donors pursuing their own self-interest leads to a collectively inefficient distribution of aid.

Equilibria emerge under a wide array of strategic responses. Both donors might engage in competition—giving more aid where the other donor gives more. Or they both might pass the buck—giving less aid where the other donor gives more. Or one might respond competitively to the aid of the other, while the other responds deferentially to the aid of the one.

Regardless of the direction of actor's best-responses, in the preponderance of cases competitive waste was observed: either one or both donors gave more aid than was efficient to the recipient that was a source of rival foreign policy interests, and by extension too little aid than was efficient to the recipient where donors had mutually beneficial objectives. However, collective inefficiency was not a universal result. Compared to the best distribution aid under collective optimization, while one donor did better in equilibrium, the other did worse. This fact highlights that while collective optimization yields Pareto optimal solutions, these are not always Pareto improvements upon Nash equilibria.

5.2 Empirical Implications

The model considered here reveals a variety of possible outcomes. Some empirical regularities that were consistent with the model have been considered, but several other general predictions remain as well. Two general empirical regularities in particular are implied by this strategic political economy of aid.

The first is that, if countries produce foreign policy externalities for one another through their aid allocations, then the bilateral aid disbursements of leading countries will be inextricably interdependent.

The second is that, provided this interdependence exists, the nature thereof will vary to the extent that donors pursue differing objectives through their aid allocations. Some of the foreign policy goals countries seek to promote through their aid giving are likely rival, such as attaining political influence and international prestige, while others are mutually beneficial, such as addressing the root causes of discontent and instability in recipients.

Precise predictions regarding these general regularities are difficult to come by. Yet, some general comparative statics will hold up under wide-ranging circumstances. Most notably, if the model is generalized to a greater number of recipients, much of the logic that applies for *friends* or *adversaries* is also localized to pairs or groups of recipients where donor goals are either common or rival. Meanwhile, the logic that applies for *competitors* also holds for donor decisions between pairs or groups of recipients where objectives are common with respect to one set, and rival with respect to another.

Suppose, for example, that i and j are *competitors*, and that they allocate aid to four recipients; not just two. In this case, i has the following marginal utilities over recipients:

$$
\begin{aligned}
MU_i^w &= \frac{\sigma_i^w}{w_i + \eta^w w_j} \\
MU_i^x &= \frac{\sigma_i^x}{x_i + \eta^x x_j} \\
MU_i^y &= \frac{\sigma_i^y}{y_i + \eta^y y_j} \\
MU_i^z &= \frac{\sigma_i^z}{z_i + \eta^z z_j}.
\end{aligned}
\tag{30}
$$

Suppose $\eta^w, \eta^x > 0$, while $\eta^y, \eta^z < 0$. Any transfer that j makes to either recipient w or x will reduce i's marginal utility for giving aid to those recipients, while any transfer of aid to either y or z will increase i's marginal utility of giving aid to either of them. If this transfer is made between, say w and y, then whether i has an incentive to increase aid to one and decrease aid to the other is impossible to know without reference to i's preferences and the precise values of the externality parameters. But, if a transfer is made between w and x, or between y and z, i's incentives are far more certain. A change in j's allocation of aid between w and x would lead to substitution by i between those recipients. Further, a change in j's allocation of aid between y and z would lead to complementarity by i between those recipients.

This observation of course falls short of identifying i's equilibrium response, but the comparative statics here are of greater consequence than precise predictions. How i distributes aid *between* recipients where j's aid generates the same type of externality—rival or common—will be consistent, even if the choice between recipients where j's aid generates different types of externalities will not. This is advantageous for large-n empirical analysis. Provided the appropriate comparisons in donor giving between recipients can be made, it is in principal possible to identify when and where donors take advantage of, or seek advantage over, one another.

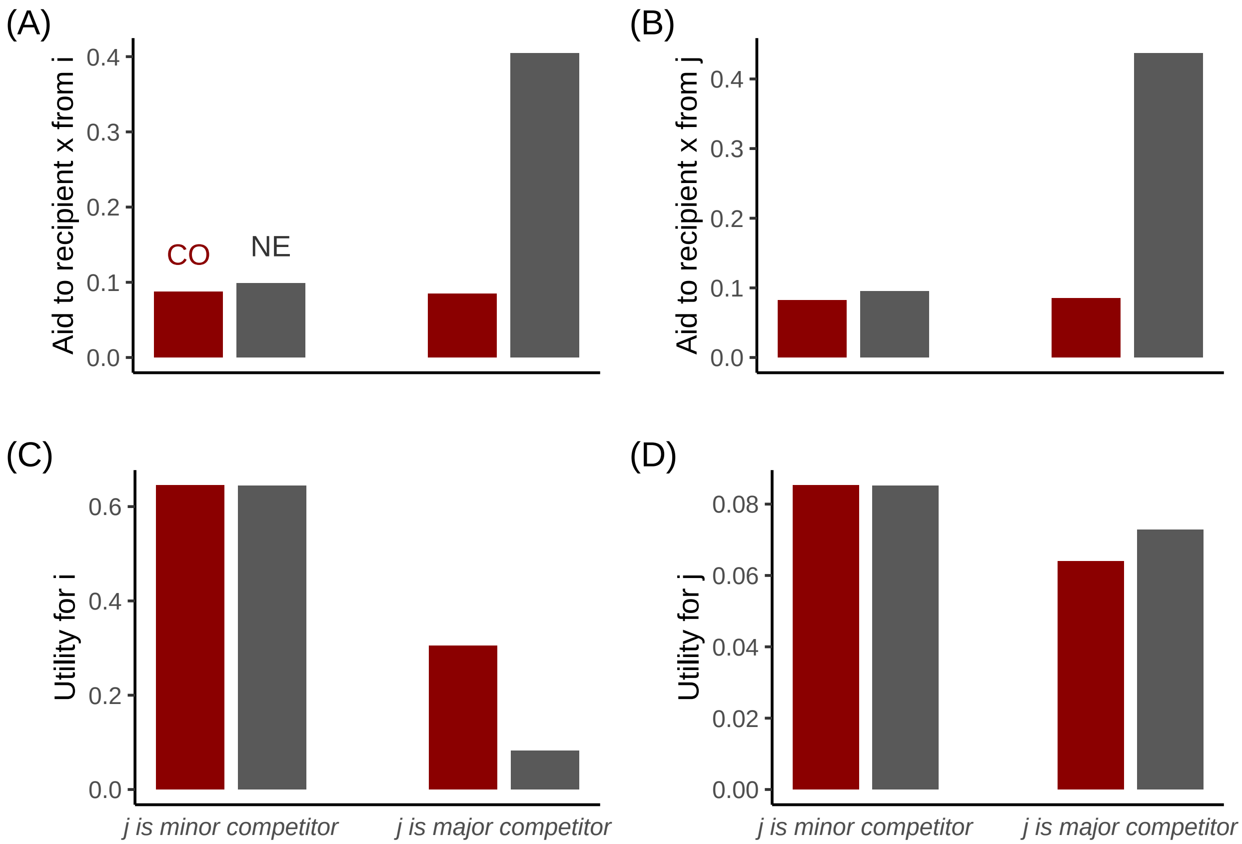

Figure 12: The rise of a major competitor is worse for everyone. CO = collective optimum. NE = Nash equilibrium.

5.3 A Final Example

This model provides practical insights as well. For instance, the model helps us answer an especially timely question: is cooperation between China and Western donor governments (namely the United States) possible?

As the results in Figure 12 suggest, the a major, relative to a minor, competitor can portend negative consequences. The figure shows what happens to donor i and j's Nash equilibrium allocations of aid to recipient x, their collectively optimal allocations of aid to x, and their utilities under these alternative distributions of aid as the balance of resources shifts away from i's favor, and the negative externality of donors' aid to x increases. Specifically, holding $\sigma_i^x = 0.1$, $\sigma_j^x = 0.5$, and $\eta^y = 0.1$, the distribution of resources is shifted from 0.9 to 0.5, and η^x is shifted from -0.1 to -0.9. These are the initial and final values of these parameters in the example of the rise of China in the comparative statics section.

In equilibrium, the governments of i and j allocate slightly more aid to x than they would under the collective solution when j is a minor competitor. Further, while the equilibrium distribution of aid is inefficient, there is an upside to this inefficiency. It implies that the collective solution yields Pareto improvements. This removes at least one barrier to cooperation.

However, the situation when j is a major competitor is not so sanguine. Given the arrangement of parameters, both donors now give much more aid to x in equilibrium than they would under the collective solution. Further, while donor i does much better if the donors would cooperatively allocate aid, donor j does better staying in equilibrium. Thus, while a collective solution exists, it fails to yield Pareto improvements.

This example demonstrates a possible barrier to cooperation with an ascendant competitor. Supposing i is an analogue for the US and j an analogue for China, this example implies that as China becomes a more prominent donor and more threatening to US interests in certain recipients, both donors will focus their energies in these recipients to the neglect of others. Further, while the US may stand to benefit from cooperation, China will stand to lose—a thought that does not bode well for future collaboration between these two donors.

6 Appendix

6.1 Proof for Proposition 0.1

Proof Following Cachon and Netessine (2004), a sufficient condition for a unique Nash equilibrium is that, for each actor the absolute value of their best-response slope is less than 1. That is:

$$\left|\frac{\partial x_i^*}{\partial x_j}\right| < 1 \forall i : i \neq j. \tag{A.1}$$

That this condition holds for the two-donor, two-recipient model detailed here is simple enough to demonstrate. Recall that δ_2 denotes the slope of i's reaction to j. We may add i and j subscripts to clarify that j has a similar parameter denoting its response to i: hence, δ_{i2} and δ_{j2}.

For country i, the identity of its reaction parameter is given as

$$\delta_{i2} = \sigma_i^x(\eta^x - \eta^y) - \eta^x. \tag{A.2}$$

From this identity, it follows that $-1 < \delta_{i2} < 1$ for all possible values of the parameters σ_i^x, η^x and η^y. This can be seen by observing the value of the reaction parameter at the limits of each η and at the limit of σ_i^x.

First, note that $\sigma_i^x \in (0, 1)$. This means that at the boundaries of this parameter, the identity of δ_{i2} converges to either $-\eta^x$ (as $\sigma_i^x \to 1$), or $-\eta^y$ (as $\sigma_i^x \to 0$).

From this, it then follows that the absolute magnitude of i's reaction parameter is limited to being no greater than that of the externality parameters. These, recall, are bound such that $\eta^x, \eta^y \in (-1, 1)$. This therefore implies that, at the limits of the model parameters, $\delta_{i2} \in (-1, 1)$. By symmetry, this necessarily implies that j's reaction is similarly bound.

Together, this meets the conditions for a unique Nash equilibrium. Therefore, the model will always have a unique Nash equilibrium solution. $\blacksquare$

6.2 Proof for Proposition 0.2

Proof Smoothness with respect to the model parameters is demonstrated by simply considering i's (and by symmetry j's) Nash equilibrium best-response x_i^*. The closed-form solution for this is given by

$$x_i^* = \frac{\delta_{i0} + \delta_{i1} R_i + \delta_{i2}(\delta_{j0} + \delta_{j1} R_j)}{1 - \delta_{i2}\delta_{j2}}. \tag{A.3}$$

From this, it is easy enough to demonstrate that x_i^* is a smooth function of the model parameters; though, an important caveat is that this smoothness is bound to best-responses such that $0 \leqslant x_i^* \leqslant R_i$. Within this range, x_i^* is differentiable with respect to the δs—and hence σ_i^x, σ_j^x, η^x, η^y—and the distribution of resources R_i. ∎

References

Alesina, Alberto, and David Dollar. 2000. "Who Gives Foreign Aid to Whom and Why?" *Journal of Economic Growth* 5(1): 33–63.

Annen, Kurt, and Stephen Knack. 2018. "On the Delegation of Aid Implementation to Multilateral Agencies." *Journal of Development Economics* 133(C): 295–305.

Annen, Kurt, and Luc Moers. 2017. "Donor Competition for Aid Impact, and Aid Fragmentation." *The World Bank Economic Review* 31(3): 708–29.

Bearce, David H., and Daniel C. Tirone. 2010. "Foreign Aid Effectiveness and the Strategic Goals of Donor Governments." *The Journal of Politics* 72(3): 837–51.

Bermeo, Sarah Blodgett. 2017. "Aid Allocation and Targeted Development in an Increasingly Connected World." *International Organization* 71(4): 735–66.

Bräutigam, Deborah A., and Stephen Knack. 2004. "Foreign Aid, Institutions, and Governance in Sub-Saharan Africa." *Economic Development and Cultural Change* 52(2): 255–85.

Cachon, Gerard, and Serguei Netessine. 2004. "Game Theory in Supply Chain Analysis." In *Tutorials in Operations Research: Models, Methods, and Applications for Innovative Decision Making*, 13–59.

Dreher, Axel, Peter Nunnenkamp, and Rainer Thiele. 2011. "Are 'New' Donors Different? Comparing the Allocation of Bilateral Aid Between nonDAC and DAC Donor Countries." *World Development* 39(11): 1950–68.

Dudley, Leonard M. 1979. "Foreign Aid and the Theory of Alliances." *The Review of Economics and Statistics* 61(4): 564–71.

Gates, Scott, and Anke Hoeffler. 2004. "Global Aid Allocation: Are Nordic Donors Different?" CSAE Working Paper Series 2004-34. Centre for the Study of African Economies, University of Oxford.

Glaser, Charles L. 2000. "The Causes and Consequences of Arms Races." *Annual Review of Political Science* 3: 251–76.

Kilby, Christopher, and Axel Dreher. 2010. "The Impact of Aid on Growth Revisited: Do Donor Motives Matter?" *Economic Letters* 107(3): 338–40.

Kisangani, Emizet F., and Jeffrey Pickering. 2015. "Soldiers and Development Aid: Military Intervention and Foreign Aid Flows." *Journal of Peace Research* 52(2): 215–27.

Lawson, Marian Leonardo. 2013. "Foreign Aid: International Donor Coordination of Development Assistance." CRS Report for Congress R41185. Congressional Research Service.

Meernik, James, Eric L. Krueger, and Steven C. Poe. 1998. "Testing Models of U.S. Foreign Policy: Foreign Aid During and After the Cold War." *The Journal of Politics* 60(1): 63–85.

Morgan, T. Clifton, and Glenn Palmer. 2000. "A Model of Foreign Policy Substitutability: Selecting the Right Tools for the Job(s)." *The Journal of Conflict Resolution* 44(1): 11–32.

Morgenthau, Hans. 1962. "A Political Theory of Foreign Aid." *The American Political Science Review* 56(2): 301–9.

Round, Jeffery I., and Matthew Odedokun. 2004. "Aid Effort and Its Determinants." *International Review of Economics and Finance* 13(3): 293–309.

Steinwand, Martin C. 2015. "Compete or Coordinate? Aid Fragmentation and Lead Donorship." *International Organization* 69(2): 443–72.

van der Veen, A. Maurits. 2011. *Ideas, Interests and Foreign Aid*. Cambridge: Cambridge University Press.

Zeitz, Alexandra O. 2021. "Emulate or Differentiate? Chinese Development Finance, Competition, and World Bank Infrastructure Funding." *The Review of International Organizations* 16: 265–92.

Competition and Buck-Passing in the Political Economy of Aid

Miles D. Williams

27 August, 2021

Abstract

When and where do donor governments compete or pass the buck in aid allocation? In this study, I answer this question using new composite measures of donor interests and recipient need for aid and a novel research design. Using a supervised machine learner (random forests) I recover evidence that DAC donors target their bilateral aid in response to where other donors target theirs on the basis of the strength of their interest in certain recipients and the depth of recipient need. Using an instrumental variables approach, I am able to further identify specifically when and where donors compete and pass the buck. Analysis reveals that donors are most reactive to peers in recipients with greatest need. Among these recipients, donors compete for rival foreign policy gains in recipients where donor interests are strongest. Meanwhile, donors defer responsibility to others in high need recipients where their interests are minimal. These findings are a novel contribution to the study of the political economy of aid and reveal strategic dynamics in donor policy that prior studies have failed to capture.

keywords: international development, political economy of aid, competition, buck-passing

1 Introduction

"Don't tell me what you value. Show me your budget, and I'll tell you what you value."[1] Joseph R. Biden Jr., then serving as U.S. Senator from Delaware, made the forgoing remark in St. Clair Shores, Michigan while stumping as Vice Presidential candidate for his running mate, Barack Obama. This wisdom, ostensibly passed down to Biden by his father, serves as the *modus operandi* for political scientists and political economists as they study the links between major powers' foreign aid budgets and their wide-ranging foreign policy goals. Country leaders regularly make proclamations about their intentions in allocating foreign aid to this or that developing country, but what leaders say they value and what they actually value are not always one in the same. How countries target their foreign aid says a great deal more about their broader interests than their leaders may relate in a foreign policy memo or speech.

By this logic, the ways in which other-country aid allocations determine when and where a single donor chooses to target its own aid say much about the broader strategic relationships that exist among donor countries. As donor governments chose how to allocate their limited aid budgets across recipients, they must base their choice not only on their respective priorities, but also in response to how other donors allocate their own aid. However, because donor governments may have rival interests in some recipients, and common interests in others, best-responses may differ across contexts. When and where do donors compete, and when and where do they pass the buck?

While a growing body of research addresses this question, progress thus far has been piecemeal at best as analyses have yielded contradictory results. Lacking in this body of work is a perspective that addresses the variable interests of donors with respect to aid recipients, and the variable positive and negative foreign policy externalities that other-country aid may generate.

[1]"Biden's Remarks on McCain's Policies" reported in *The New York Times* on Sep. 15, 2008. Accessed on Mar. 25, 2021. https://www.nytimes.com/2008/09/15/us/politics/15text-biden.html

In this study, I answer this question with the help of new composite measures of donor interests and of recipient need for aid and a novel research design. Using a supervised machine learner (random forests) I recover evidence that DAC donors make their aid allocation on the basis of the giving of other DAC members, and that these responses vary systematically with respect to the strength of donor interests and the depth of recipient need. Using an instrumental variables approach, I further am able to identify specifically when and where donors compete and pass the buck. I find that donors are most responsive to where peers target their aid in recipients with greatest need. Among these recipients, donors compete in recipients where donor interests are strongest, and defer responsibility in recipients where their interests are minimal.

These findings reveal strategic dynamics in donor policy that prior studies have failed to capture. Further, they help to adjudicate between alternative perspectives on both the targeted and diffuse interests of donor governments. They show that donors may give greatest weight to strategic and material foreign policy goals when giving aid to high need recipients that have the strongest economic, strategic, social, and geographic ties to donor governments. Conversely, when the importance of these factors is minimal, donor governments seem to share a common interest in addressing recipient need. This pattern is consistent with other studies that have attempted to identify when and where donors place greater importance on their strategic goals or responding to development need (Bearce and Tirone 2010; Girod 2012; Heinrich 2013). However, this study does not rule out alternative explanations.

After presenting results, I conclude with a discussion of possible threats to inference, and stress the need for continued research. The methods used in this study are powerful but not beyond reproach. Future studies might take a regional perspective to studying inter-donor strategy and consider alternative ways of measuring donor interest and recipient need.

2 Donor Strategy in the Political Economy of Aid

This study is not the first to address the question of how foreign aid donors react to the giving of others. However, it is unique in situating this question within a more general framework that considers varying donor interests, and varying positive and negative externalities with respect to individual recipients.

In contrast, some of the earliest efforts to identify how major countries respond to one another when they allocate aid center on total aid giving, rather than on aid given to specific recipients. As a consequence, these studies speak only to broad trends in aid expenditures and say very little about the foreign policy goals motivating aid giving to particular recipients (see Dudley 1979; Mosley 1985).[2] The conclusion of these early studies was that foreign aid donors spend more in total on aid when peers do as well, but they proposed different mechanisms for this behavior. Dudley (1979), for example, proposed competition for rival foreign policy concessions, while Mosley (1985) proposed "peer pressure."

More recent studies complicate, and in some cases contradict, these conclusions. Many of the more recent efforts to identify the strategic behavior of foreign aid donors apply both more sophisticated econometric techniques, and analyze bilateral aid allocations. These approaches allow for richer analysis and hypothesis testing, but despite methodological advances and improvements in research design, these studies yield inconsistent answers. Some find evidence of competition, others of buck-passing, and some find a mix when examining individual donors or breaking the analysis down by aid delivery channel (see Barthel et al. 2014; Davies and Klasen 2019; Frot and Santiso 2011; Fuchs, Nunnenkamp, and Öhler 2015; Steinwand 2015; Mascarenhas and Sandler 2006; Rahman and Sawada 2012). More recently, some studies have focused on competition between the U.S. and China (Zeitz 2021).

[2] To be fair, this choice no doubt partially reflects computational limitations at the time these studies were published.

Taken as a whole, these studies each assess inter-donor reactions in varied ways. However, individually, they emphasize either a constrained set of donor goals, or allow for little variation in how donors react across different contexts. Steinwand (2015) stands out as a notable exception, given the author's focus on how donor "leadership" and aid channels may condition responses. However, the role of recipient characteristics, and of donors' wide-ranging recipient-specific goals, remains untested.

Donor governments allocate aid for a mix of political and humanitarian reasons. However, certain goals will differ in importance between aid recipients. In some cases donors will have rival interests, while in others donors will have common interests. *Common* goals are any objectives that are collectively beneficial—when one country takes actions to realize a certain goal, this by extension helps another country get closer to realizing its goal as well. Aid given to support green energy projects in recipient countries, for example, might represent a mutually beneficial objective. Climate change, after all, has consequences for the entire international community, and efforts taken by one government to address this challenge creates a positive externality for others.

Alternatively, *rival* goals are those where one state's gain is another's loss. For example, during the Cold War, the United States and the Soviet Union pursued various goals that were *rival* in nature. As geopolitical antagonists, competition manifested in how the super powers targeted foreign aid—the U.S., for example, gave much more aid to authoritarian countries than it would have otherwise to counter Soviet influence (Bräutigam and Knack 2004).

3 Predictions for Donor Interactions

The above implies some straightforward regularities in the way donor governments target their foreign aid across recipient countries:

1. How countries allot aid across recipients is interdependent;

2. In recipients where donor goals yield common benefits, donors will have incentives to pass the buck (to target less aid where peers target more).
3. In recipients where donor goals yield rival benefits, donors will have incentives to compete (to target more aid where peers target more).

The first prediction can be expressed as a simple, testable hypothesis. To the extent that donor governments' aid allocations generate foreign policy externalities:

> H_{int}: *How a donor targets aid across recipient countries is dependent on how other countries target theirs.*

The matter of how to approach the second pair of regularities is less obvious. If interdependence in country aid allocations differs systematically with the objectives donor governments pursue, there will be some set of recipients where donors show deference to one another, and there will be another set of recipients where donors compete. The problem is how to identify when and where which type of response is present.

Decades of research reveals many clues about the types of objectives donor governments pursue. Kilby and Dreher (2010) enumerate several, such as fighting terrorism, supporting strategically valuable regimes, and promoting good relations with major trade partners. Other goals include supporting and maintaining influence over former colonies (Round and Odedokun 2004), gaining international prestige and recognition (van der Veen 2011), minimizing diffuse spillovers of recipient country problems (Bermeo 2017), and complementing and legitimizing military operations (Kisangani and Pickering 2015). Outside of the specific goals of countries, it is also possible to think of donor motives as either rooted in selfish interests or humanitarianism pending how salient strategic donor goals are relative to the need of a recipient (Heinrich 2013).

While we know much about donor interests, we know little about when these interests are rival or common. It is imaginable that objectives like gaining prestige in the international community and exercising diplomatic influence are rival. Meanwhile, interest in responding to recipient needs may be of mutual interest. Of course, the wrinkle is that many of these goals may coexist within a given aid donor's relationship with an individual developing country. Empirically, this makes it hard to tease apart how countries respond to each other with respect to their specific goals in isolation. Instead, it is really only possible to observe how countries react given the overall basket of objectives they pursue by giving aid to certain recipients. This necessitates an empirical strategy that, short of identifying specific objectives, can reliably capture variation in the factors that may make the overall basket of goals countries pursue in certain aid recipients on net *rival* or *common*.

To this end, it is helpful to have composite measures that summarize two key factors underlined in much of the aid literature. Traditionally, donor motives are organized under two umbrellas. These are donor *interest* and relative recipient *need*. The first concept reflects the strategic, economic, social, and geographic considerations that enter into donor government evaluations of where they should prioritize development finance. Component variables that capture variation these goals include bilateral trade, geographic proximity, colonial heritage, and alliances. These factors span the range of countries' goals with respect to aid recipients. Recipient need, meanwhile, is captured by factors like poverty, population size, the presence of ongoing violent conflict, the occurrence of major natural disasters, and lack of political and civil liberties.

Donor interests and recipient need will vary in magnitude between recipients, and their unique combination in recipients will likely be associated with different foreign policy goals donors emphasize. By extension, their combination will influence donors' strategic responses to each other.

> H_{het}: *Interdependence between donors' aid allocations will vary with respect to recipient* **need** *and donor* **interest**.

However, the nature of this interaction is necessarily a matter of speculation, and thus exploratory analysis. Some alternative perspectives imply different predictions.

One perspective follows from the *targeted development* framework (Bermeo 2017). This view holds that since the turn of the century, industrialized countries have increasingly emphasized international development in their grand strategies. The reason is that deepening connections between industrialized and developing countries make the former distinctly susceptible to the consequences of poverty, discontent, and violence in the latter. This has been especially true in the last few decades. As a consequence, Bermeo (2017) argues that donor governments increasingly see promoting development abroad—specifically, in developing countries whose problems pose the greatest threat—as essential to ensuring national security at home. This leads policymakers in industrialized states to prioritize giving foreign aid, not only to needy recipients, but specifically to needy recipients with strong bilateral connections to the donor. This view does not preclude other political or strategic motivations for aid allocation, but it does imply that such goals may be superseded by development when recipient needs pose a threat.

This implies two things. First, donors will have greater mutual interest among recipients with greater need for aid *and* with which they share strong ties (as captured by donor *interest*). Second, to the extent that donors have nondevelopment goals (political, economic, strategic), donors will have rival interest in recipients with less need for aid *but* that have greater importance to donor governments.

An alternative perspective follows from the aid-for-policy exchange perspective presented by Bueno de Mesquita and Smith (2009). In this view, donor governments use foreign aid as a "bribe" to leverage desired policy changes or concessions from recipient governments. The value of such concessions will vary between recipients, but are likely to be greatest when and where recipients are important to donors for economic, social, or strategic reasons.

Recipient factors matter in this perspective, too. Specifically, recipients with greater need will be preferred targets for aid-for-policy deals; but, not necessarily because donors seek to address recipient needs. Rather, greater need simply means donor governments have greater leverage to yield policy concessions (Bueno de Mesquita and Smith 2009).

These concessions may not be mutually beneficial for donors. Even among allies, donor governments have conflicting goals. One German aid official, for instance, complained about his country's diminished diplomatic influence on development policies in Bangladesh due to the greater giving of other DAC donors (Steinwand 2015). Thus, under the aid-for-policy exchange view, it is pluasible that recipient need and donor interest will coincide with rival objectives for donor governments—and, therefore, will lead to donor competition.

However, just as targeted development does not preclude nondevelopment interests, aid-for-policy exchange does not preclude interest in development. As former U.K. Prime Minister David Cameron noted several years ago, failure to promote development abroad means "the problems of conflict, the problems of mass migration, the problems of uncontrollable climate change are problems that will come and visit us at home."[3] This is a view that has been explicitly expressed by many donor governments, and is suggestive of a generalized "enlightened self-interest" mentality toward international development. It is possible, then, that while donors have targeted strategic or material interests with respect to some recipient governments, they may have a more diffuse interest in international development when strategic goals are less salient. Several studies, in fact, provide evidence consistent with this view, showing that aid from donors is more likely to translate into positive development outcomes for recipients when and where donors' strategic interests are less important (Bearce and Tirone 2010; Girod 2012).

This view implies two predictions. First, among the neediest recipients, donor goals will be rival in nature where donor *interest* is greatest. Second, among needy recipients where donor interests are minimal, donors may stand to mutually benefit from promoting development.

[3] Remarks made during the United Nations High-Level Panel of Eminent Persons on Post-2015 Development Agenda held September 25, 2012.

Table 1: Plausible Reactions among Aid Donors

Interest and Need	*Targeted Development*	*Aid-for-Policy Exchange*
High Interest/High Need	$-$	$+$
High Interest/Low Need	$+$	?
Low Interest/High Need	?	$-$
Low Interest/Low Need	?	?

Cell entries denote the expected sign of donor reactions.

The predictions implied by this pair of views are shown in Table 1. The signs denote the direction of the anticipated reaction by a given donor to the aid of others. Some of these cells have an unknown sign, since the precise implications of these perspectives are unclear for these combinations of donor *interest* and recipient *need*.

The analysis that follows cannot hope to prove any of the above perspectives true, but results may be more or less consistent with one than with the other. Before proceeding with the analysis, however, the next section briefly summarizes the data and the construction of the measures used to assess heterogeneity in donors' strategic responses.

4 The Data

To test the hypotheses proposed in the previous section, and to explore the specifics of donor interactions, an original dataset was constructed with variables from multiple databases. The outcome of interest, denoted *aid*, is measured using the bilateral foreign aid commitments of the 29 Development Assistance Committee (DAC) member countries reported in the Creditor Reporting System (CRS), a database maintained by the Organization for Economic Co-operation and Development (OECD). The CRS database provides self-reported data on the aid committed (and disbursed) by DAC countries to individual aid recipients. It further provides data on the development sectors aid is targeted toward in a way that is consistent and comparable for all DAC members.

The choice to focus on DAC countries is made in light of a few, but salient, logistical realities. First, DAC countries are certainly not the only countries or organizations to allocate foreign aid, but they are by any objective measure the most prominent in terms of total aid contributions. This means that when they consider where to target their foreign aid, they are most apt to do so in reference to the aid allocations of fellow DAC members—though the case of China is a notable exception (Zeitz 2021).

Second, DAC countries have committed to consistently and transparently reporting on their aid allocations. From a measurement perspective, this puts reliance on the CRS database on solid footing. Though other databases exist that cover a wider set of donors, reporting by these other donors is not always reliable.

Bilateral aid commitments across 24 key sectors from 1995 (the first year countries started reporting to CRS) to 2014 are included in the measure of *aid* and are normalized to 2017 U.S. dollar values. Further, commitments are operationalized at the level of the donor-recipient-year. Commitments are used in stead of disbursements since the latter may lag substantially behind the more immediate changes in policy revealed in donor commitments. Commitments themselves represent written assurances donors make, in dollar amounts, to contribute to recipient countries in a given year.

Like most financial data, the distribution of aid is highly skewed and censored at zero. To normalize outcomes while also retaining zero values, bilateral aid commitments are transformed using the inverse-hyperbolic sine (ihs). Much like the logarithmic transformation often applied in analyses of foreign aid, using the ihs transformation permits interpreting estimates as elasticities, or percent changes in the response given changes in the model predictors. However, unlike the log-transformation, ihs preserves zero values without having to introduce unnecessary distortions to the data, like adding 1 dollar to all of the response values.

Aid data is used not only to construct the response, but also the sum of aid giving by all other donors to a recipient. In the analysis that follows, these values are distinguished from one another in the following way: while aid_{irt} denotes bilateral aid commitments from donor i to recipient r at time t, aid_{-irt} denotes bilateral aid commitments from all donors other than i to recipient r at time t. The latter is also normalized via the ihs transformation.

To capture donor *interest* and recipient *need*, rather than rely on separate component measures of each, I develop two composite measures that capture variation in both concepts. The measures of recipient *need* and donor *interest* were constructed using variables drawn from multiple datasets. *Need* is comprised of the following variables, each measured at the level of aid recipients:

- yearly per capita gross domestic product (GDP);
- yearly population size;
- the yearly number of individuals killed due to natural disasters;
- an indicator for whether the recipient is experiencing a civil war in a given year;
- the yearly level of political and civil liberties of a recipient.

The first two measures were drawn from the Penn World Table (version 9.1), and were log-transformed to normalize values (no zero values occur in either, permitting application of the log-transformation rather than ihs). The third, which captures the severity of natural disasters in a given year, is drawn from the Institute of Health Metrics and Evaluation's database on natural disaster deaths reported by countries in a given year. Values are transformed via ihs. The indicator for civil war is drawn from the UCDP/PRIO armed conflict database. It takes the value 1 for all years where there was a violent conflict between at least two parties that involved the deaths of at least 25 combatants and which included the government as at least one of the parties in the conflict. The final measure, recipient civil and political liberties, is the sum of the Freedom House's political rights and civil liberties scores for a given recipient country in a given year. The rights and liberties scores each range from 1 to 7, with higher values denoting more violations. After summing the values, the scores were reversed so that higher values denote greater freedom.

The donor *interest* measure, meanwhile, was constructed from the following four variables:

- bilateral distance (in kilometers) between a donor and a recipient;
- bilateral trade (in dollars) between a donor and a recipient;
- an indicator for whether the donor and recipient are formal allies;
- an indicator for whether the donor and recipient share a colonial past.

The first and second measures were taken from CEPII. Distance comes from CEPII's gravity dataset, and trade comes from CEPII's TRADEHIST dataset. The former is log-transformed, while the latter is transformed via ihs. The alliance measure is drawn from the ATOP database and takes the value 1 if the donor and recipient share an alliance. The colony measure comes from the same CEPII dataset as the bilateral distance measure, and takes the value 1 if the donor was a former colonizer of the recipient.

To construct the *need* and *interest* measures, I devised an algorithm based on other common techniques of feature projection—namely, principal components analysis and multiple factor analysis. In brief, the goal of the algorithm is to construct a continuous measure that is optimized to covary as much as possible with any single component measure without detracting too much from its covariance with any one of the other component measures. Specifically, for each component variable x_{ik} with $i = 1, ..., n$ observations for $k = 1, ..., m$ variables, the algorithm identifies a set of parameters $\omega = (\omega_1, ..., \omega_m) \in \mathbb{R}^m$ that maximize

$$\sum_{k=1}^{m} \text{cov}(x_{ik}, z_i), \tag{1}$$

where z_i is the linear combination of the m variables:

$$z_i = \sum_{k=1}^{m} \omega_k x_{ik}. \tag{2}$$

To help ensure that variables are on a comparable scale, each is mean-centered and transformed to have standard deviation of 1—even the binary measures. After it is generated, the linear combination z_i is also mean-centered and transformed to have standard deviation of 1. It can be helpful to think of this approach as generating a weighted index from component measures, where the algorithm identifies the appropriate weights, and the most appropriate sign, to give to each component.

The resulting composite captures much, though of course not all, of the information contained in the variables used to construct it. Overall, these measures perform well as predictors of aid allocation, and their covariance with their component measures is largely consistent with the direction of each separate measure's relationship with aid allocation (see results in the Appendix). This happy coincidence follows from the fact that the component measures also generally covary in ways consistent with their relationship with aid commitments. Poorer countries usually are also larger, less free, more likely to experience civil war, and likely to suffer more deaths due to natural disasters. Further, trade, alliances, proximity, and colonial past also tend to go hand-in-hand. See the correlation tables in the Appendix for a summary.

Two discrepancies in the construction of these variables bear noting. The first is with respect to *need* and centers on the Freedom House measure. The optimal linear combination for *need* is constructed such that greater rights and liberties are associated with less need. However, a common finding in the aid literature is that donors tend to give more aid to freerer countries, which is a relationship I also recover (results shown in the Appendix). Even so, when taking steps to account for this discrepancy by manually reversing the sign on the generated weight for the Freedom House measure, the relationship between *need* and aid commitments is severely attenuated, and the overall variance explained in aid commitments declines by almost 10 percentage points. This suggests that incorporating lower freedoms as prognostic of greater need for aid is, in fact, valid and contributes to greater precision in predicting donor priorities.

The second discrepancy is with respect to *interest*. In this measure, an alliance between a donor and recipient is related to greater donor interest in a recipient. However, the direct influence of alliances on bilateral aid is negative and statistically insignificant as shown in the "Components" model in table A.5 in the appendix. As a check for a potentially negative relationship between alliances and aid, I made a modified version of the *interest* measure where alliances received a negative, rather than positive weight. This modified version of donor *interest* performs much worse than the original measure, as the results shown under the "Modified 2" column show in the regression table in the appendix. This suggests that alliances may indeed be a component of donor interest, even if its individual performance as a predictor of donor giving is weak.

Overall, the benefit of creating these measures is that they substantially simplify analysis of heterogeneity in aid donor reactions to the bilateral aid commitments of others. Estimating this heterogeneity with respect to multi-way interactions across nine different variables would not only use up valuable degrees of freedom, but would also severely limit interpretation of the results. The idea behind whittling the analysis down to two measures is to support meaningful interpretation; albeit, at a minor cost to predictive power. As estimates (shown in the Appendix) reveal, the composite measures explain about 5% less variation in the response than do the separate component measures.

On the point of interpretation, the variables used to construct *need* and *interest* are all relatively uncontroversial predictors of where donor countries target their foreign aid. The components of *need* capture salient factors that determine the relative need that developing countries have for foreign aid. The idea is that larger, poorer countries; those experiencing severe and deadly natural disasters and enduring civil war; and those lacking in political rights and civil liberties should be in greater need of donor assistance. Meanwhile, the components of *interest* capture features of donor-recipient relationships that make recipients especially attractive targets of foreign aid. Specifically, more geographically proximate countries, those that are lucrative trade partners, those that are allies, and former colonies should be sites of greater donor interest, and thus recipients of greater aid.

5 Methods

The analysis proceeds in two parts. First, tests for the two main hypotheses are considered: (H_{int}) that countries' aid allocations are interdependent, and (H_{het}) that this interdependence is heterogeneous with respect to recipient characteristics and donor interests. After testing the hypotheses, the analysis then turns to an exploration of heterogeneity in donor responses. The below sections summarize the methods used for each set of analyses.

5.1 Hypothesis Testing with Random Forests

The approach I take to testing the two main hypotheses is unconventional, but nonetheless robust. Specifically, I use random forest (RF) regression and associated diagnostics to recover evidence in support of the hypotheses. RF is a workhorse machine learning technique that constructs an ensemble of decision-tree regressions computed on repeated bootstrapped samples of the data and subsets of model predictors. The overall fit of the model is the average over the individual tree predictions—hence, the name random "forest." This approach is uniquely powerful compared to many other popular machine learners since bootstrapping and "bagging" (averaging) predictions helps to avoid overfitting and is robust to outliers (Scornet 2016). The method was first introduced by Breiman (2001) and has since been applied by scholars across scientific fields and disciplines, even among political scientists (see Bonica 2018; Carroll and Kenkel 2019; and Hill and Jones 2014).

The strength of RF within the context of testing the above hypotheses is that it is nonparametric. This means it imposes no functional form on the data-generating process *ex ante*. Rather, the algorithm identifies "buckets" into which to divide the data that optimize model predictions.

This nonparametric approach to estimation is a relevant feature in testing for interdependence in aid allocations; although, the reason why may not appear obvious at first. For instance, with respect to the first hypothesis, why not use standard spatial econometric techniques like a linear spatial autoregressive model? To briefly summarize, the parameter of interest in such a model is often denoted ρ, where, given a matrix of geographic weights $\mathbf{W}$, a response is regressed on a set of covariates and what is called a spatial lag (the response for other individuals in the data). Often, the model is estimated via OLS. If the recovered $\rho \neq 0$, this counts as evidence of statistically significant spatial dependence in the response—that is, the response for one individual is affected by the responses for all others, or those for which the geographic weights are greater than zero.

The problem with this approach in this context is that it assumes, given the appropriate weights, that ρ is constant. If, however, there is heterogeneity in the spatial dependence of the response, ρ may be biased. For example, suppose the recovered spatial lag is not statistically different from zero. This could count as evidence against significant spatial dependence, *or* it could disguise unobserved heterogeneity. Since the focus here is on how countries distribute aid across a wide range of recipients, substantial variation in spatial dependence across recipients would lead to misleading estimates of ρ.[4] After all, this is what the second hypothesis predicts. For this reason, a linear model is not the most useful approach.

Using RF side-steps this issue. Rather than estimate a single spatial lag parameter, it is possible to measure the overall prediction error of the RF model with and without using the sum of peer aid commitments to a given recipient as a covariate predicting where and how much aid an individual donor commits. A significant improvement in predictive power due to accounting for peer aid would be consistent with the first hypothesis (H_{int})—and this, without having to explicitly specify the form of the relationship between individual and other-donor aid commitments.

Fox, Ver Hoef, and Olsen (2020) summarize some prior studies that have compared RF to spatial regression. In some cases, RF proved superior in terms of prediction error,

[4] Prior studies that examine donor interactions take some version of this approach, which may explain why they yield conflicting results.

while in others spatial regression was more efficient. However, the authors note that the studies that compare these methods only assess prediction performance without considering changes to model defaults. Further, they fail to take an informed approach to variable transformations or data exploration. For this reason, Fox, Ver Hoef, and Olsen caution against making too much of these prior comparisons. Their own analysis suggests that both types of approaches have value; though, RF in particular has an edge when dealing with nonlinearities that are difficult to address with data transformations alone, or when exploring complex patterns and interactions in the data. Given the anticipated, but unknown form of, complexity in donor interdependence, RF thus confers an advantage.

While RF is nonparametric, it does have a number of hyper (tuning) parameters that are specified by the analyst prior to estimation. Some common parameters to tune include the number of trees to "grow," the number of variables to split a tree by at a given node, and the minimal tree node size. Statistical software usually specifies default values for each; however, these defaults may not be optimal across all contexts. Optimizing these parameters requires doing a grid search over different values and seeing which combination best minimizes prediction error. To optimize RF performance, when fitting RF models I perform an iterative search over possible values for these three hyper parameters and select the combination that provides the smallest prediction error.

After fitting RF models, there are several ways of calculating the predictive importance of a given factor used in model estimation. To assess the importance of peer aid, in particular, I consider two metrics:

1. Percent accuracy of out-of-sample predictions;
2. The permutation importance of model predictors.

To compute the first metric, I subset the data into what are called "training" and "test" datasets. The first consists of all observations in the data from 1995 to 2010. The second consists of all observations from 2011 to 2014.[5]

[5]This choice is arbitrary. The objective is to train the model on enough of the data so that it will yield

I then train two RF models using the training data. For one, the response is a function of

$$\text{aid}_{irt} = f(\text{interest}_{irt}, \text{need}_{rt}, \text{Donor}_i, \text{Budget}_{it}), \tag{3}$$

where $Donor_i$ is a set of donor indicators and $Budget_{it}$ is total ODA spending per donor per year (ihs).[6] The second model is like the first, except it also includes the aid commitments of other DAC countries to a given recipient in a given year as a predictor of the aid committed by an individual donor i:

$$\text{aid}_{irt} = f(\text{aid}_{-irt}, \text{interest}_{irt}, \text{need}_{rt}, \text{Donor}_i, \text{Budget}_{it}). \tag{4}$$

After training both models, I evaluate the predictive performance of each using the test dataset. Specifically, I generate a set of predictions for 2011-2014 aid commitments with each trained model and calculate the percent accuracy of the predictions. This is estimated simply as

$$\%\text{Accuracy} = 100 \times \text{cor}(\widehat{\text{aid}}_{irt}, \text{aid}_{irt})^2, \tag{5}$$

where $\widehat{\text{aid}}_{irt}$ are the 2011-2014 predictions for aid commitments.

The second metric I use is called "permutation importance." It captures the increase in prediction error due to permuting the values of a given predictor. This can be calculated using an algorithm proposed by Fisher, Rudin, and Dominici (2019). The approach entails:

1. training a model,
2. calculating its mean squared error (MSE),

quality predictions in the test data.

[6] This is used in place of year indicators because RF is not well suited to extrapolation. Since year indicators for 2011-2014 are out-of-sample for the training data, year indicators would have zero prognostic power in the test data.

3. permuting a given covariate,
4. generating new predictions and calculating the new MSE,
5. calculating the difference between the original MSE and the new.

The larger the difference calculated in step 5, the more a variable contributes to the predictive power of the model. The idea is that permuting a factor breaks its relationship with the response. As a result, to the extent that said factor was important for predicting the response, the model will make more severe prediction errors when that variable is permuted. A greater loss in predictive power after permuting a factor means that it was especially prognostic of the response.

By iterating the permutation process, it is also possible to generate a distribution of permutation importance estimates. This makes it possible to do statistical inference. With respect to testing H_{int}, if the permutation importance of peer aid is statistically distinguishable from zero, this will count as evidence of interdependence in donor aid allocations.

In practice the approach to computing permutation importance can be applied either on the training dataset, or the test dataset. The major difference is that using the test set is likely to result in a noisier measure of permutation importance, and hence a more conservative estimate. I therefore opt for the latter since this will constitute a harder test of the interdependence hypothesis.

Turning to the second hypothesis, H_{het}, the approach to testing for the presence of interactions between peer aid and donor *interest* and recipient *need* is a little more involved. Friedman and Popescu (2008) propose estimating what they call an H-statistic. The theory behind the statistic is simple; though, in practice it can be computationally taxing to estimate. One of its key strengths, however, is that it is model-agnostic, and hence not limited in application to any one particular estimator or model.

The null hypothesis for H holds, simply, that there is no variation in the response explained by some function $f(x_{i1}, ..., x_{ik})$ that cannot be explained by the sum of factor-specific functions $f_1(x_{i1}) + ... + f_k(x_{ik})$. In other words, the whole is *not* greater than the sum of its parts. The alternative hypothesis is that there is some non-zero fraction of variation in the response that can only be accounted for by allowing for interactions among covariates. Which is to say, formally, $f(x_{i1}, ..., x_{ik}) \neq f_1(x_{i1}) + ... + f_k(x_{ik})$.

There is a little more to the specific equation for H proposed by Friedman and Popescu (2008), and interested readers are directed to their paper for a summary. However, in principal their formulation is not terribly complicated. What is complicated is the process of estimating H in practice. It involves the use of partial dependence functions, usually denoted $PD_x(x_k) = N^{-1} \sum_{i=1}^{N} f(x_k, x_{-ki})$. In words, the partial dependence function captures the marginal variation in a response given a single predictor k, averaging over the prediction given all other covariates. Generating the partial dependencies demands a great deal of computational power and time, especially when calculated for a learner algorithm like RF. Even a dataset with tens of thousands of individual observations (small by big-data standards) is large enough to make the process unfeasible, or at the very least impractical.

I therefore take a slightly modified approach. Instead of averaging over all possible predictions for predictor k, given all possible values taken by other model factors, I divide the sample by donor and year, and calculate for a given variable, or set of variables in the case of allowing for interactions, predicted values over the observed variables of interest, holding all other variables at their mean. For instance, for a hypothetical variable x_k, I compute

$$f_k(x_{ik}) = f(x_{ik}; \bar{x}_{-k}). \tag{6}$$

This gives the predicted response over variation in x_{ik}, holding all else constant.

As an additional corrective, it helps to center the partial predictions at a value that will be consistent across all sets of partial predictions to be compared. Specifically, this means calculating

$$\bar{f}_k(x_{ik}) = \bar{f}(x_{ik}; \bar{x}_{-k}) = f(x_{ik}; \bar{x}_{-k}) - f(\bar{x}_k; \bar{x}_{-k}), \tag{7}$$

which demeans the prediction by the conditional predicted mean of the response holding all covariates (including k) at their mean.

Following the formulation proposed by Friedman and Popescu (2008), I begin by testing for second-order interactions between peer aid and the measures of *need* and *interest*. This is done by estimating a two-way H-statistic. For a pair of variables j and k, this is calculated as

$$H^2_{\text{2-way}} = \frac{\sum_{i=1}^{N} \left[\bar{f}_{jk}(x_{ij}, x_{ik}) - \bar{f}_j(x_{ij}) - \bar{f}_k(x_{ik})\right]^2}{\sum_{i=1}^{N} \bar{f}_{jk}(x_{ij}, x_{ik})^2}. \tag{8}$$

The calculated H^2 denotes the fraction of the variance unexplained by the additive predictions that can be accounted for by allowing for variable interactions.

I further test for a three-way interaction among the covariates of interest. The equation for a three-way H-statistic is slightly modified, but quite similar in form to the above. For three variables j, k, and l:

$$\begin{aligned} H^2_{\text{3-way}} = \sum_{i=1}^{N} [&\bar{f}_{jkl}(x_{ik}, x_{ik}, x_{il}) - \bar{f}_{jk}(x_{ij}, x_{ik}) - \bar{f}_{jk}(x_{ij}, x_{il}) - \bar{f}_{jk}(x_{ik}, x_{il}) \\ &+ \bar{f}_j(x_{ij}) + \bar{f}_k(x_{ik}) + \bar{f}_l(x_{il})]^2 \\ / \sum_{i=1}^{N} &\bar{f}_{jkl}(x_{ij}, x_{ik}, x_{il})^2. \end{aligned} \tag{9}$$

The above three-way H^2 denotes the fraction of variance unexplained by assuming only second-order interactions. A non-zero value means there is variance in the response accounted for by assuming a three-way interaction beyond that accounted for by separate two-way interactions.

In practice, $\bar{f}$ is significantly faster to compute than partial dependencies. This comes in handy, not only for quickly estimating the above H-statistics, but also for doing statistical inference. The H-statistic has no known distribution, meaning one must be simulated, for example via bootstrapping the predictions. Because $\bar{f}$ takes relatively little time to compute, bootstrapping a distribution for the H-statistic requires relatively little additional time as well. This is done simply by resampling the data, generating new predictions, and re-estimating H^2.

5.2 Identifying When Donors Compete and Pass the Buck

Assuming the above analysis fails to reject the null of no three-way interaction—that is, assuming I find that $H^2_{\text{3-way}} \neq 0$—I then estimate the following linear model via two-stage least squares (2SLS):

$$\begin{aligned}
\text{aid}_{irt} = {} & \beta_1 \text{aid}_{-irt} + \beta_2 \text{interest}_{irt} + \beta_3 \text{need}_{rt} \\
& + \gamma_1 (\text{aid}_{-irt} \times \text{interest}_{irt}) + \gamma_2 (\text{aid}_{-irt} \times \text{need}_{rt}) \\
& + \gamma_3 (\text{interest}_{irt} \times \text{need}_{rt}) \\
& + \nu (\text{aid}_{-irt} \times \text{interest}_{irt} \times \text{need}_{rt}) \\
& + \delta_i + \tau_t + \epsilon_{irt},
\end{aligned} \tag{10}$$

where a first stage equation models peer aid (aid_{-irt}) as a function of the exogenous variables and an instrumental variable Z_{irt}.

Identifying the appropriate instrument is the key challenge. Aid studies that have examined reactions to other-donor aid expenditures typically rely on the aggregate GDP of other donors. This is, generally speaking, a strong instrument—it does a good job of predicting the aggregate giving of other donors and, in theory, satisfies the exclusion restriction since other-donor GDP is unlikely to directly affect how much an individual country spends on aid.

However, peer GDP is a poor instrument for identifying donor reactions in how they allocate aid across developing countries. Peer GDP provides no between-recipient exogenous variation that we can exploit to identify how peer aid influences how an individual donor targets its own foreign aid.

An alternative choice is using aggregate peer *interest*. The effect of peer *interest* on where an individual donor targets its aid is plausibly exogenous to the extent that its relationship with where an individual donor gives aid is mediated through its effect on aggregate peer giving across recipients. Aggregate peer *interest* likewise should be a good predictor of aggregate peer giving.

Thus, the first-stage equation is specified as

$$\begin{aligned}
\text{aid}_{-irt} = {} & \beta_1 \text{interest}_{-irt} + \beta_2 \text{interest}_{irt} + \beta_3 \text{need}_{rt} \\
& + \gamma_1(\text{interest}_{-irt} \times \text{interest}_{irt}) + \gamma_2(\text{interest}_{-irt} \times \text{need}_{rt}) \\
& + \gamma_3(\text{interest}_{irt} \times \text{need}_{rt}) \\
& + \nu(\text{interest}_{-irt} \times \text{interest}_{irt} \times \text{need}_{rt}) \\
& + \delta_i + \tau_t + \epsilon_{irt},
\end{aligned} \tag{11}$$

where $interest_{-irt}$ is simply the sum of other-donor affinity for a given recipient in a given year:

$$\text{interest}_{-irt} = \sum_{j=1}^{D-1} \text{interest}_{jrt} : j \neq i \text{ and } D = \text{No. of donors.} \tag{12}$$

There is no diagnostic test that can prove the above is a valid instrument; however, it is at the very least possible to assess its power to predict variation in the endogenous variable and whether estimation via 2SLS is more efficient than simply using OLS. On both of these counts, diagnostics shown in the Appendix indicate that peer *interest*, indeed, is a strong instrument, and that the 2SLS estimator is more efficient than OLS.

The model is rounded off with donor and year fixed effects. The former account for slow-moving unobserved donor characteristics determining overall foreign aid giving. These also ensure that estimates reflect within donor variation in the response. The year indicators, meanwhile, account for unobserved yearly shocks that may influence overall donor giving.

To account for heteroskedasticity and dependence of observations within dyads (donor-recipient pairs), inference for model estimates is done via robust standard errors, clustered by dyad.[7]

The primary parameter of interest is the marginal relationship between peer ODA and individual donor ODA given variation in *interest* and *need*. The range of values identified will reveal when and where donors engage in strategic complementarity (competition) or substitution (deference) between recipient countries.

6 Results

6.1 Heterogeneous Interdependence

I begin by summarizing the results for H_{int}—that the giving of aid donors is interdependent. Evidence consistent with this hypothesis is shown in Figures 1 and 2. The first compares the prediction accuracy of random forest (RF) models trained to predict ODA commitments. One model was fit with peer ODA commitments as a predictor, while the other was not. Each was trained using observations from 1995 to 2010, and predictions were made for observations from 2011 to 2014. The training set consisted of 3,678 donor-recipient pairs, or dyads, and 52,132 total observations. The test set consisted of 3,218 dyads and 12,872 total observations. Summary statistics for the data are shown in the Appendix.

Without accounting for peer ODA, the trained RF model is able to predict around 60% of the variation in 2011-2014 ODA commitments of individual DAC members. While not bad, the model that was trained using peer ODA as a factor performs better. It is able to

[7]Specifically, CR1 standard errors are used.

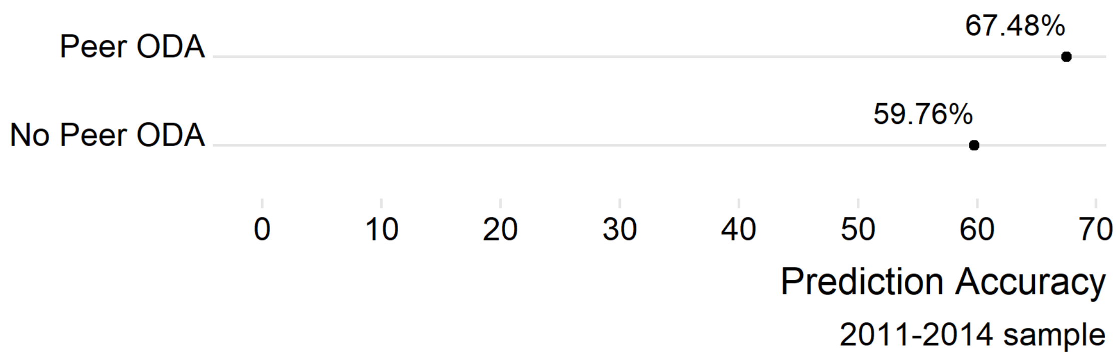

Figure 1: Accuracy of predictions for the 2011-2014 sample with Random Forests models trained on 1995-2010 observations.

predict over 67% of the variation in aid commitments. This is not a titanic improvement to be sure, but a six percentage point gain in accuracy is worth noting.

The predictive importance of Peer ODA is further supported by the results shown in Figure 2. For each of the model factors, the average permutation importance after 100 iterations is shown along with 95% confidence intervals. Recall that the permutation importance measures the increase in residual mean squared error (MSE) for the model predictions due to permuting each of the factor values. Essentially, it measures the worsening of prediction error if the relationship between a factor and the response is broken.

As the results shown in Figure 2 suggest, peer ODA is the second most important predictor—the most important being the a donor's yearly "budget" (importance equals 0.87). The average permutation importance for peer ODA is 0.35. This is double that for *interest* (0.17) and *need* (0.17). The identity of the donor was least predictive, with a permutation importance of 0.1.

Because iteratively permuting factors generates an empirical distribution for the importance metric, we can further use the confidence bands to infer whether the importance of a factor is statistically distinguishable from zero. For all factors other than year, the increase in prediction error due to permuting is, indeed, statistically significant. This counts as further evidence that the aid commitments of DAC countries are influenced by the commitments of fellow DAC members.

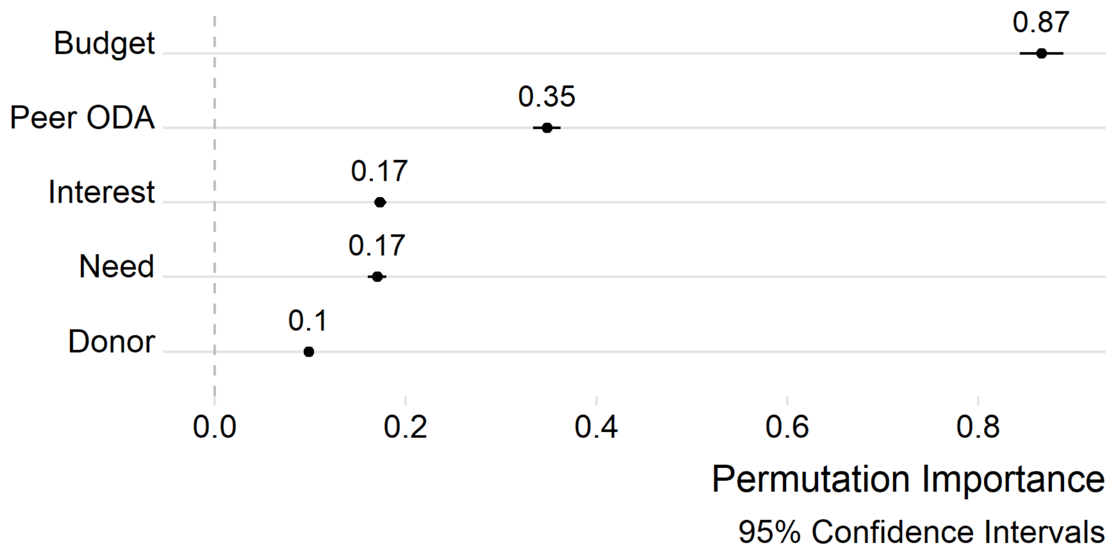

Figure 2: Permutation importance of model factors. Importance evaluated using 2011-2014 predictions.

Of course, beyond confirming interdependence in country aid allocations, we also are interested in whether this interdependence varies systematically with the factors motivating donor giving to particular aid recipients. Specifically, H_{het} holds that donors should condition their aid allocation on peer giving in reference to their political, economic, colonial, and geographic ties with recipients (captured by *interest*) and in reference to the development needs of recipients (captured by *need*).

Figure 3 shows donor specific estimates of the H^2 statistic described in the previous section. Recall that this statistic denotes the fraction of variance in the response that cannot be accounted for by assuming either no variable interactions or only lower-order reactions. Across all donors for the 2011-2014 period, H^2 for a two-way interaction between peer ODA and *need* is non-zero and statistically significant. However, results for a two-way interaction between peer ODA and *interest* are not as strong. While the relevant H^2 statistics are all greater than zero, this estimate is only statistically significant for about half of the donors. Even so, there is strong evidence in support of a three-way interaction among peer ODA, *interest*, and *need*. The relevant H^2 statistics are all greater than zero and statistically significant.

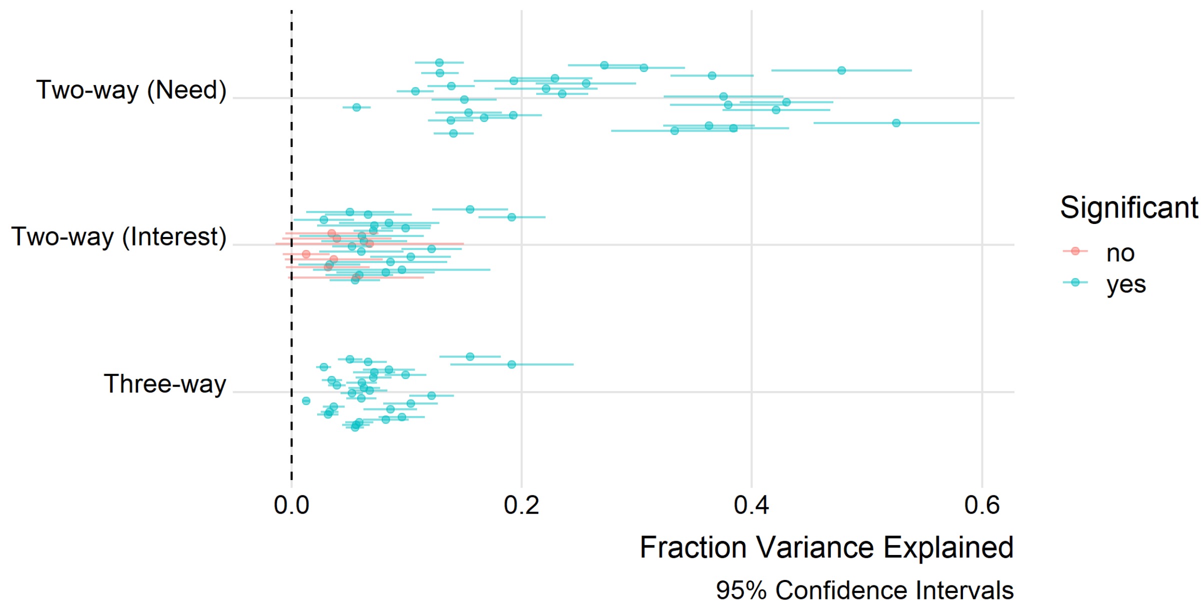

Figure 3: Computed H^2 values for intereaction effects, calculated using test dataset predictions.

To make these results a little more concrete, it is helpful to highlight estimates for some of the leading DAC countries in the sample. Figure 4 shows the estimated H^2 statistics for France, Germany, Japan, the United Kingdom, and the United States. For each county, there is evidence in support of, at the very least, a two-way interaction between peer ODA and recipient *need*. Meanwhile, there is evidence of a significant two-way interaction between peer ODA and donor *interest* for all donors other than the U.K. All five donors show evidence of a three-way interaction among the variables of interest.

Taken together, these results support the view that donors not only condition where they commit bilateral aid based on where other DAC countries commit theirs, but also that their strategic response to peer aid is conditioned by the salience of their strategic, economic, diplomatic, and geographic interests, and by the relative neediness of a given recipient. However, they do not reveal the specific ways that these factors influence donor interactions across developing countries. To recover estimates of how responses vary, the analysis now turns to more conventional econometric tools—specifically, instrumental variables regression.

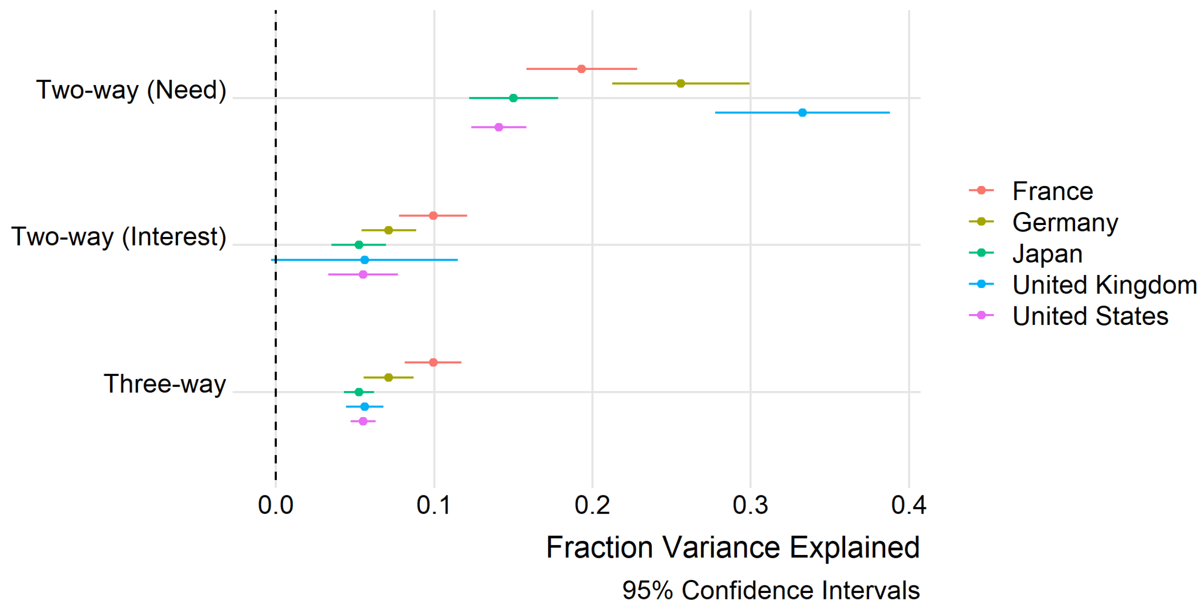

Figure 4: H^2 statistics for five prominent DAC countries—France, Germany, Japan, the United Kingdom, and the United States.

Recall the regression model specified in the previous section. This model included a three-way interaction among peer ODA, donor *interest*, and recipient *need*. This specification permits identifying the conditional response of donors to where fellow DAC members commit greater aid. However, to avoid bias in estimates, it is necessary to account for interdependence (endogeneity) in donor giving. To do this, peer ODA is instrumented with the sum of peer *interest* for individual recipients. This permits estimating a *local* average response to peer ODA given variation in the aggregated interest that other donors have for particular recipients.

Before turning to the results, it will be helpful to revisit the two theoretical arguments about donor objectives considered earlier: (1) *targeted development* and (2) *aid-for-policy exchange*. These two views make different predictions about which set of factors motivating donor giving dominate the other. Targeted development holds that when and where recipient needs pose a threat to a donor, donor governments will prioritize development promotion. Conversely, to the extent that donors have other strategic, economic, or diplomatic goals they will be free to pursue them in recipients with lower development need.

Aid-for-policy exchange holds that donor governments prioritize policy concessions in strategically, economically, or diplomatically important recipients. Further they will have greatest leverage to promote their interests in recipients with greatest need for aid. To the extent that donors do care about development, they will have an interest in addressing recipient need in recipients where nondevelopment goals are a lower priority.

These perspectives imply different patterns of donor government responses to peer aid. The first is consistent with donor competition in low need recipients where donors have high interest, and buck-passing in high need recipients where donors have high interest. The second is consistent with donor competition in high need recipients that are important to donors, and buck-passing in high need recipients where donor interests are less important.

The results shown in Figure 5 are most consistent with the second perspective. It appears that the externality generated by peer aid is most pronounced among the neediest recipients, while donor ties with recipients determine whether this externality is positive or negative.

The figure shows the marginal relationship between peer ODA and individual donor aid commitments holding *interest* and *need* at different levels.[8] Low values denote one standard deviation below the mean, while high values denote one standard deviation above the mean.

In low *need* contexts, regardless of whether *interest* is low or high, the estimate for peer ODA is not statistically distinguishable from zero—as suggested by the overlap between the 95% confidence intervals and zero along the y-axis. However, in high *need* contexts, among recipients that are less strategically important to donors, those that receive one percent greater total aid from fellow DAC members receive nearly 2 percent less aid from an individual donor. Conversely, among important recipients, those that receive one

[8]This relationship is, of course, *local* to observations where peer giving is most explained by total peer *interest*.

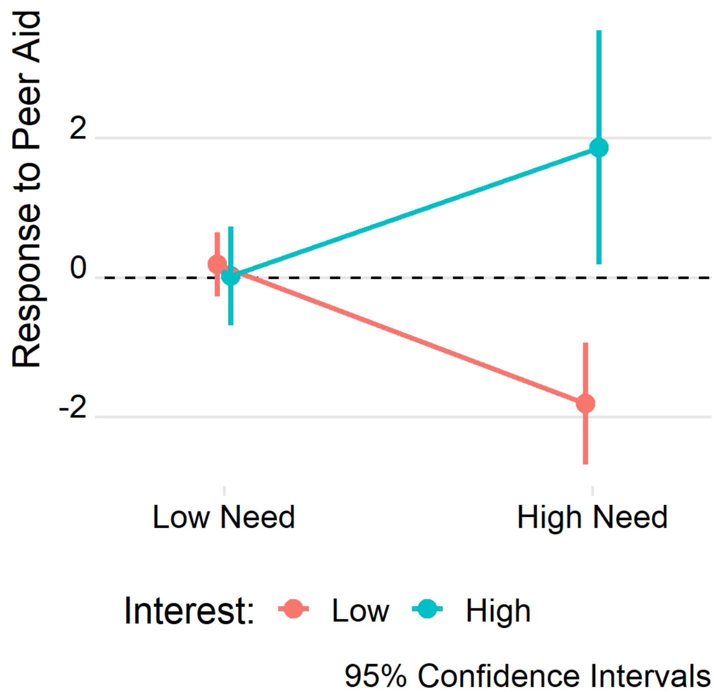

Figure 5: 2SLS estimates with robust 95% confidence intervals clustered by dyad. High and low values denote plus or minus one standard deviation relative to the mean respectively.

percent greater aid from fellow DAC members also receive nearly 2 percent more aid from an individual donor.

These findings suggest that when a recipient has greater need for aid, and when factors that make non-development goals more salient to donors are present—like promoting and maintaining trade, supporting an ally, maintaining a presence in a former colony, or supporting a geographically proximate country—aid appears to promote rival objectives among donors. As a result, the more aid that peers give to a recipient, the harder an individual donor has to work to promote its interests. Conversely, when donor interests are minimal and recipient need is the primary determinant of aid, donor governments respond deferentially to others.

7 Discussion

7.1 What Do These Findings Mean?

Overall, this study demonstrates two regularities in the political economy of aid: (1) as countries pursue wide-ranging foreign policy goals through their bilateral aid allocations, their commitments are highly interdependent, and (2) that interdependence varies with the degree of rivalry or commonality of donor objectives. The idea that states pursue a mix of rival and common objectives through aid allocation is certainly not controversial, or new. The more difficult task has been to identify when and where donors respond competitively or deferentially to the aid allocations of others. This study's primary contribution has not only been its confirmation that the strategic relationships among donors are heterogeneous over recipients, but also its identification of *when* and *where* rivalry and buck-passing are most pronounced.

Specifically, the results suggest that the primary arena for strategic responses is among the neediest developing countries. Further, among these aid recipients, the constellation of donor interests summarized by their relative *interest* for recipients conditions whether they see peer aid as a net help or hindrance. Among recipients where donor interests in promoting factors like trade, supporting allies, maintaining diplomatic ties with former colonies, and helping close neighbors are most salient, countries view peer aid as a threat. As a result, among the DAC members analyzed, donor governments compete in these recipients, giving more aid where fellow DAC members give more, all else equal. The converse is observed among recipients where donors' nondevelopment interests are less salient. DAC members pass the buck in recipients where strategic interest is low, but recipient need for aid is relatively high.

These findings have intuitive appeal, and are most consistent with an *aid-for-policy exchange* perspective of donor giving. In this view, donor governments have an interest in leveraging policy concessions from important recipients, while they may retain a generalized interest in addressing recipient need when and where donors' nondevelopment goals are less salient. This pattern is consistent with other studies that identify when and where donors place greater importance on their strategic objectives or on responding to development need (Bearce and Tirone 2010; Girod 2012; Heinrich 2013). These prior studies underline how donor governments' nondevelopment interests distract from interest in promoting development.

However, on the basis of this study alone it is impossible to rule out the alternative perspective: *targeted development.* Two explanations consistent with *targeted development* may account for the pattern of donor responses identified here. First, nondevelopment and development goals may complement each other (Bermeo 2018). As a result, donors may have an incentive to compete for nondevelopment concessions, even in recipients where they also care most about promoting development.

Second, it is possible that while it is in donor governments' mutual interest to promote development, they may have conflicting preferences over the implementation of development policies in recipients (Steinwand 2015). If this is the case, donors will have an incentive to compete to ensure that recipient development unfolds in a way that they think is most appropriate and effective.

7.2 Threats to Inference

However compelling these results, the usual cautionary note applied to analyses of observational data holds here as well. It should go without saying that interdependence in donor aid allocations could just be the artifact of omitted variables bias; although, it seems unlikely that DAC members would ignore the aid allocations of one another when making their own aid commitments.

More troubling for the robustness of these findings might be arguments centered on the fragility of the 2SLS estimates that purportedly identify when and where countries engage in strategic substitution or complementarity. Such criticism would be well taken.

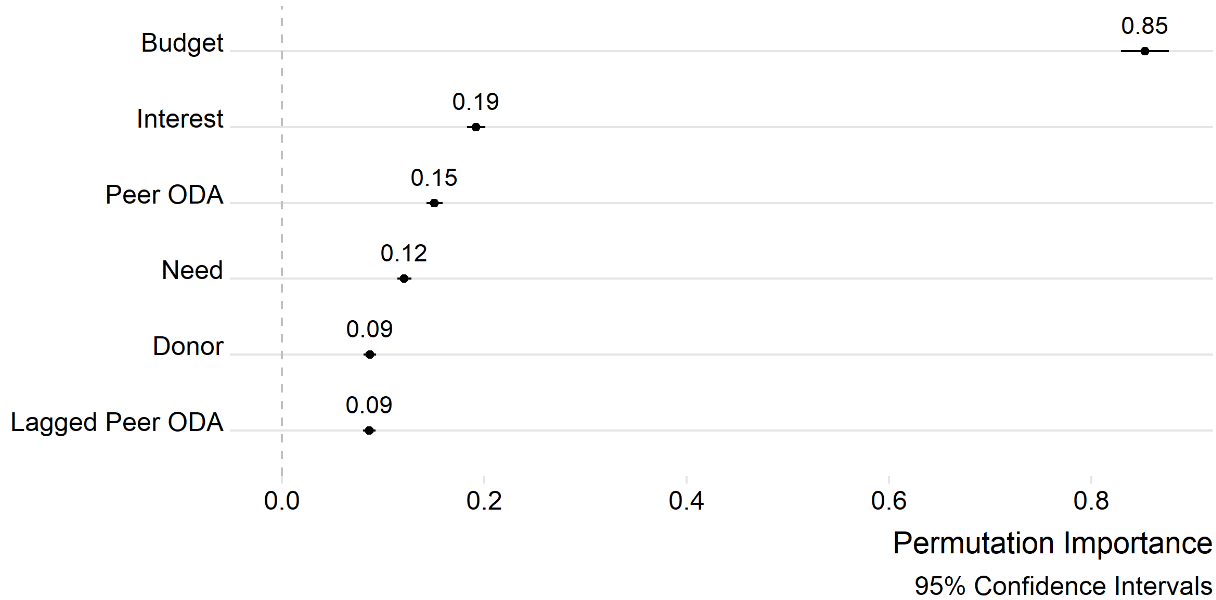

Figure 6: Permutation importance including lagged peer ODA as a factor.

For example, suppose the concern with using total peer *interest* as an instrument centered on its exogeneity. It could be argued that aspects of interest, namely bilateral trade, are endogenous to the aid allocations of DAC members.

There are two counters to this claim. The first is that endogeneity, if it does exist in the relationship between trade and foreign aid, applies to aid *disbursements* rather than aid *commitments* (Barthel et al. 2014). This line of reasoning follows from the fact that commitments precede disbursements, and disbursements are more likely to have an effect on trade. The second response is that the component measure of trade has been lagged by a year in the construction of donor interest.

Of course, these points are open to debate. The fact that commitments precede disbursements does not preclude a more direct causal role of commitments in promoting trade. Further, though a common strategy in observational studies, lagging variables is certainly not a magic bullet (see Bellemare, Masaki, and Pepinsky 2017).

A more satisfying solution to this problem could be to use a plausibly exogenous component of the *interest* measure as an instrument instead. The sum of the bilateral

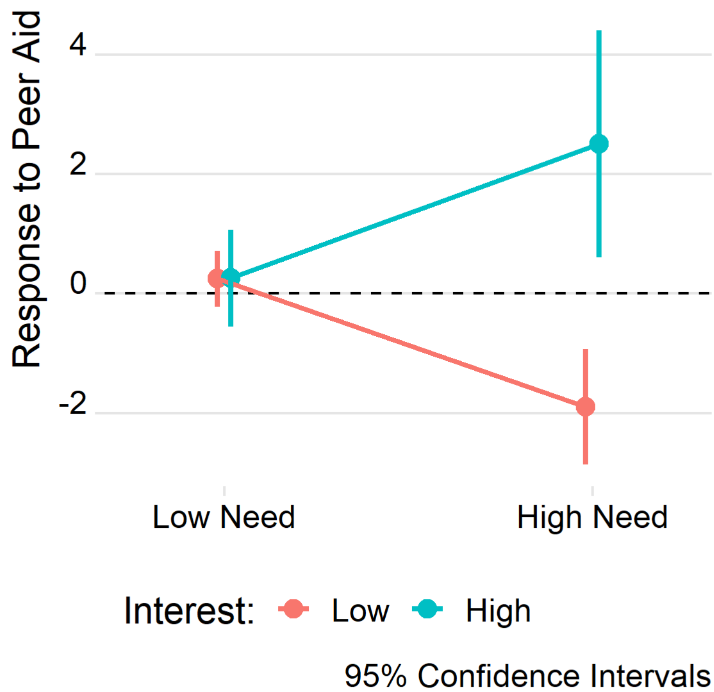

Figure 7: 2SLS estimates using the five year lag of total peer *interest* as an instrument. Robust 95% confidence intervals shown, clustered by dyad.

distances between other DAC members and an individual recipient, for instance, might be an appropriate choice. No one could argue that aid commitments *cause* geography, so in this sense aggregate peer distance from recipients seems a strong contender. However, a limitation of bilateral distance is that, while it varies between recipients, it does not vary over time. It therefore can only account for enduring patterns in donor aid allocations, but not new developments in donor priorities that evolve over time. Using distance would only further limit the generalizability of the already *local* estimate obtained through 2SLS.

Another option might be to use the lag of peer ODA as an instrument for contemporary commitments. Using the lag of an explanatory variable has been applied when no known or other viable instrument can be found (for instance, Braumoeller 2008). This approach, however, assumes that there is no dynamic dependence at work in the response. It is possible that donors make their aid allocations not only on the basis of where others give aid in a given year, but also on the basis of their past allocations (Davies and Klasen 2019).

One way to check against this possibility is to include the lag of peer ODA commitments as a factor predicting individual donor aid allocations. Permutation importance estimates for a trained RF model that includes lagged peer ODA as a factor are shown in Figure 6. While including lagged peer ODA seems to diminish the importance of within-year peer allocations, the overall importance of lagged peer ODA is the smallest. When checking the predictive performance of the model, its performance is relatively unchanged relative to the model that excludes the lag of peer ODA.

It is tempting to conclude from these results that there is no substantial dynamic dependence in the response; however, this claim would be premature. It is impossible to rule out dynamic dependence based on these results alone, and lagged peer commitments do seem to account for some of the variation in where donors commit aid.

Perhaps the least problematic solution (though it certainly is still problematic) is using a deep lag of total peer *interest* as an instrument. This avoids the dynamic dependence problem associated with using the lag of the response, and also the time-invariant problem associated with using the sum of peer distance (albeit with a time delay). A lag of five years, for example, may be far enough removed from the contemporary choices of donors to minimize endogeneity. Figure 7 shows 2SLS estimates using this modified instrument. Notably, an unfortunate consequence of using the 5 year lag of peer *interest* is the loss of the first five years in the dataset. However, despite this loss of data, the estimates remain mostly unchanged—though a little noisier with wider 95% confidence intervals. This does not prove that peer *interest* is an appropriate instrument, but it is encouraging that the patterns reported in the main analysis hold up with an alternative specification, and a slightly truncated sample.

8 Conclusion

In their seminal essay, Alesina and Dollar (2000) asked whether "the pattern of aid flows [is] dictated in large part by political and strategic considerations which have little to do with rewarding good policies and helping the more efficient and less corrupt regimes in developing countries" (33). Their own analysis led the authors to conclude that, indeed, political and strategic factors played outsized roles in determining where leading countries targeted their foreign aid. Though by the term "strategic" Alesina and Dollar did not have in mind interactions among donors per se, the analysis summarized here confirms that inter-donor strategy also plays a significant role in dictating how countries distribute foreign aid.

Much work remains to be done to understand the decisions that lead to the patterns in donor responses identified in this study. This study applies many new methods and measures to the question of donor strategy. For this reason, all the more scrutiny and continued research is demanded to confirm and refine this analysis.

9 Appendix

Tables A.1 and A.2 show summary statistics. A.3 shows the correlation matrix for the measure of recipient *need* with its component measures, and A.4 shows the correlation matrix for the measure of donor *interest* with its component measures.

Table A.5 shows OLS estimates with robust clustered standard errors for five regression models. These were estimated with the panel dataset of donor aid commitments. The first model was estimated using only donor and year fixed effects. The second adds the composite measures of *interest* and *need*. The third and fourth replace these measures with alternative constructions of *need* and *interest* respectively. The final model is estimated with the separate components of *interest* and *need*.

Table A.6 shows model fit diagnostics for 2SLS estimates, both for the main analysis and the robustness check using the 5-year lag of peer *interest* as an instrument. Table A.7 shows the 2SLS estimates with robust-clustered standard errors for each model. Donor and year fixed effects are not shown.

A.1: Summary of Observations

	N	Dyads	Donors	Recipients
Training Set	52,132	3,678	29	127
Test Set	12,872	3,218	28	115

A.2: Summary Statistics

		Mean	Median	SD	Min.	Max.
Training Set	Interest	-0.02	-0.33	1.00	-1.87	5.79
	Need	0.02	-0.01	1.01	-2.14	2.75
	ODA	1.06	0.01	1.69	0.00	10.14
	Peer ODA	5.54	5.80	1.86	0.00	10.71
	Total Budget	5.60	7.21	3.67	0.00	10.84
Test Set	Interest	0.07	-0.27	1.00	-1.87	5.16
	Need	-0.07	-0.05	0.94	-2.04	2.15
	ODA	1.25	0.17	1.79	0.00	10.47
	Peer ODA	5.89	6.09	1.79	0.20	10.71
	Total Budget	6.55	7.16	2.74	0.00	11.21

A.3: Correlation Matrix for Need

	Need	Income	Population	Disaster	Freedom	Civil War
Need	1.000	-0.696	0.720	0.550	-0.437	0.609
Income	-0.696	1.000	-0.161	-0.030	0.218	-0.170
Population	0.720	-0.161	1.000	0.628	-0.305	0.357
Disaster	0.550	-0.030	0.628	1.000	-0.026	0.267
Freedom	-0.437	0.218	-0.305	-0.026	1.000	-0.235
Civil War	0.609	-0.170	0.357	0.267	-0.235	1.000

A.4: Correlation Matrix for Interest

	Interest	Distance	Trade	Colony	Alliance
Interest	1.000	-0.822	0.384	0.249	0.791
Distance	-0.822	1.000	-0.146	-0.026	-0.424
Trade	0.384	-0.146	1.000	0.134	0.163
Colony	0.249	-0.026	0.134	1.000	0.013
Alliance	0.791	-0.424	0.163	0.013	1.000

A.5: Multilevel Tobit Estimates

	ODA Commitments				
	F.E. Only	Main	Modified 1	Modified 2	Components
Recipient Characteristics					
Need		0.55^{***}		0.54^{***}	
		(0.02)		(0.02)	
Mod. Need			-0.10^{***}		
			(0.02)		
Income					-0.27^{***}
					(0.02)
Population					0.22^{***}
					(0.01)
Disaster					0.04^{***}
					(0.01)
Freedom House					0.03^{***}
					(0.00)
Civil War					0.14^{***}
					(0.04)
Bilateral Characteristics					
Interest		0.19^{***}	0.15^{***}		
		(0.02)	(0.02)		
Mod. Interest				0.03	
				(0.02)	
Distance					-0.29^{***}
					(0.03)
Trade					0.01^{*}
					(0.00)
Colony					1.99^{***}
					(0.13)
Alliance					-0.10
					(0.06)
Constant	0.62^{***}	0.76^{***}	0.75^{***}	0.60^{***}	4.85^{***}
	(0.13)	(0.11)	(0.13)	(0.12)	(0.38)
R^2	0.35	0.46	0.36	0.45	0.51
Adj. R^2	0.35	0.46	0.36	0.45	0.51
Num. obs.	65004	65004	65004	65004	65004
RMSE	1.38	1.26	1.37	1.27	1.20
N Clusters	3678	3678	3678	3678	3678

$^{***}p < 0.001$; $^{**}p < 0.01$; $^{*}p < 0.05$. Donor and year fixed effects not shown. Standard errors are robust and clustered by dyad.

A.6: 2SLS Diagnostics

	df1	df2	statistic	p-value
Main 2SLS Fit				
Weak Instrument (Peer ODA)	4	64950	319.1312	0
Weak Instrument (Peer ODA $\times$ Interest)	4	64950	1268.8144	0
Weak Instrument (Peer ODA $\times$ Need)	4	64950	678.0863	0
Weak Instrument (Peer ODA $\times$ Interest $\times$ Need)	4	64950	972.3944	0
Wu-Hausman (Endogeneity)	4	64946	845.7504	0
2SLS with Lagged Instrument				
Weak Instrument (Peer ODA)	4	46939	272.9340	0
Weak Instrument (Peer ODA $\times$ Interest)	4	46939	1278.0597	0
Weak Instrument (Peer ODA $\times$ Need)	4	46939	609.2691	0
Weak Instrument (Peer ODA $\times$ Interest $\times$ Need)	4	46939	846.7482	0
Wu-Hausman (Endogeneity)	4	46935	666.3831	0

A.7: 2SLS Estimates with Clustered S.E.

	Main Specification	Lagged Instrument
Peer ODA	0.07 (0.37)	0.28 (0.40)***
Interest	-5.54 (1.74)**	-7.18 (2.12)***
Need	0.67 (1.12)	-0.02 (1.18)
Peer ODA $\times$ Interest	0.88 (0.28)**	1.10 (0.33)***
Peer ODA $\times$ Need	-0.04 (0.14)	0.02 (0.13)
Affinity $\times$ Need	-5.73 (1.36)***	-7.05 (1.69)***
Peer ODA $\times$ Interest $\times$ Need	0.96 (0.23)***	1.10 (0.27)***
Num. obs.	65004	46988

$^{***}p < 0.001$; $^{**}p < 0.01$; $^{*}p < 0.05$

References

Alesina, Alberto, and David Dollar. 2000. "Who Gives Foreign Aid to Whom and Why?" *Journal of Economic Growth* 5(1): 33–63.

Barthel, Fabian, Eric Neumayer, Peter Nunnenkamp, and Pablo Selaya. 2014. "Competition for Export Markets and the Allocation of Foreign Aid: The Role of Spatial Dependence Among Donor Countries." *World Development* 64(C): 350–65.

Bearce, David H., and Daniel C. Tirone. 2010. "Foreign Aid Effectiveness and the Strategic Goals of Donor Governments." *The Journal of Politics* 72(3): 837–51.

Bellemare, Marc F., Takaaki Masaki, and Thomas B. Pepinsky. 2017. "Lagged Explanatory Variables and the Estimation of Causal Effect." *Journal of Politics* 79(3): 949–63.

Bermeo, Sarah Blodgett. 2017. "Aid Allocation and Targeted Development in an Increasingly Connected World." *International Organization* 71(4): 735–66.

———. 2018. *Targeted Development: Industrialized Country Strategy in a Globalizing World*. New York: Oxford University Press.

Bonica, Adam. 2018. "Inferring Roll-Call Scores from Campaign Contributions Using Supervised Machine Learning." *American Journal of Political Science* 62(4): 830–48.

Braumoeller, Bear F. 2008. "Systemic Politics and the Origins of Great Power Conflict." *The American Political Science Review* 102(1): 77–93.

Bräutigam, Deborah A., and Stephen Knack. 2004. "Foreign Aid, Institutions, and Governance in Sub-Saharan Africa." *Economic Development and Cultural Change* 52(2): 255–85.

Breiman, Leo. 2001. "Random Forests." *Machine Learning* 45: 5–32.

Bueno de Mesquita, Bruce, and Alastair Smith. 2009. "A Political Economy of Aid." *International Organization* 63(2): 309–40.

Carroll, Robert J., and Brenton Kenkel. 2019. "Prediction, Proxies, and Power." *American Journal of Political Science* 63(3): 577–93.

Davies, Ronald B., and Stephan Klasen. 2019. "Darlings and Orphans: Ineractions Across

Donors in International Aid." *Scandinavian Journal of Economics* 121(1): 243–77.

Dudley, Leonard M. 1979. "Foreign Aid and the Theory of Alliances." *The Review of Economics and Statistics* 61(4): 564–71.

Fisher, Aaron, Cynthia Rudin, and Francesca Dominici. 2019. "All Models Are Wrong, but Many Are Useful: Learning a Variable's Importance by Studying an Entire Class of Prediction Models Simultaneously." http://arxiv.org/abs/1801.01489.

Fox, Eric W., Jay M. Ver Hoef, and Anthony R. Olsen. 2020. "Comparing Spatial Regression to Random Forests for Large Environmental Datasets." *PLoS ONE* 15(3).

Friedman, Jerome H., and Bogdan E. Popescu. 2008. "Predictive Learning via Rule Ensembles." *The Annals of Applied Statistics* 2(3): 916–54.

Frot, Emmanuel, and Javier Santiso. 2011. "Herding in Aid Allocation." *Kyklos* 64(1): 54–74.

Fuchs, Andreas, Peter Nunnenkamp, and Hannes Öhler. 2015. "Why Donors of Foreign Aid Do Not Coordinate: The Role of Competition for Export Markets and Political Support." *The World Economy* 38(2): 255–85.

Girod, Desha M. 2012. "Effective Foreign Aid Following Civil War: The Nonstrategic-Desperation Hypothesis." *American Journal of Political Science* 56(1): 188–201.

Heinrich, Tobias. 2013. "When Is Foreign Aid Selfish? When Is It Selfless?" *The Journal of Politics* 75(2): 422–35.

Hill, Daniel W. Jr., and Zachary M. Jones. 2014. "An Empirical Evaluation of Explanations for State Repression." *American Political Science Review* 108(3): 661–87.

Kilby, Christopher, and Axel Dreher. 2010. "The Impact of Aid on Growth Revisited: Do Donor Motives Matter?" *Economic Letters* 107(3): 338–40.

Kisangani, Emizet F., and Jeffrey Pickering. 2015. "Soldiers and Development Aid: Military Intervention and Foreign Aid Flows." *Journal of Peace Research* 52(2): 215–27.

Mascarenhas, Raechelle, and Todd Sandler. 2006. "Do Donors Cooperatively Fund Foreign Aid?" *The Review of International Organizations* 1: 337–57.

Mosley, Paul. 1985. “The Political Economy of Foriegn Aid: A Model of the Market for a Public Good.” *Economic Development and Cultural Change* 33(2): 373–93.

Rahman, Aminur, and Yasuyuki Sawada. 2012. “Can Donor Coordination Solve the Aid Proliferation Problem.” *Economics Letters* 116(3): 609–12.

Round, Jeffery I., and Matthew Odedokun. 2004. “Aid Effort and Its Determinants.” *International Review of Economics and Finance* 13(3): 293–309.

Scornet, Erwan. 2016. “On the Asymptotics of Random Forests.” *Journal of Multivariate Analysis* 146: 72–83.

Steinwand, Martin C. 2015. “Compete or Coordinate? Aid Fragmentation and Lead Donorship.” *International Organization* 69(2): 443–72.

van der Veen, A. Maurits. 2011. *Ideas, Interests and Foreign Aid*. Cambridge: Cambridge University Press.

Zeitz, Alexandra O. 2021. “Emulate or Differentiate? Chinese Development Finance, Competition, and World Bank Infrastructure Funding.” *The Review of International Organizations* 16: 265–92.